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Military Communities and Natural Hazards in the United States

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ABSTRACT

The vulnerability and resilience of communities to hazards is a concept that has gained traction in the research community in recent decades. Climate change, combined with increasing damages from natural hazards, has energized researchers and practitioners alike to identify the risks to people and places from future losses. Military communities support large military bases and are composed of service members, their families, and civilian populations alike. Due to the presence of military installations and military populations, the characteristics of the population and influences in military communities are unique. However, there is a gap in current research to assess whether the unique characteristics of military populations and places extend to the underlying social vulnerability and resiliency in the community and what the contributing factors are. Additionally, hazard losses in military communities and their relative hazardousness has yet to be identified, even though significant disasters have negatively impacted military bases and communities in recent years.

Hazard losses, social vulnerability, and community resilience are the three components in the hazardousness of military communities that are explored in this research. Hazard losses are quantified using the Spatial Hazard Events and Losses Database for the United States (SHELDUS), while social vulnerability and resilience use the Social Vulnerability Index (SoVI®) and the Baseline Resilience Indicators for Communities (BRIC) as their measures. SoVI and BRIC enable relative comparisons between places and are the best available indices designed to measure the multidimensional constructs of social

vulnerability and resilience, respectively. Descriptive statistics, inferential statistics, and spatial statistics were performed to assess differences in the variables.

Military communities have significantly lower levels of hazard losses and social vulnerability than other communities in the United States, while significant differences in community resilience were not detected. When exploring the factors of social vulnerability, lower age dependency and higher service sector employment are the main contributors to those differences regardless of location. Air Force communities are the most socially vulnerable to hazards among military communities, while Navy communities, which are located along the coasts and have higher amounts of wealth, are the least socially vulnerable. For resilience, lower amount of community capital in military communities is the dominant factor and is consistent across geographies. Navy communities demonstrate the lowest resiliency levels, driven by significantly lower levels of community capital. In contrast, Army communities have the highest levels and are mostly located in high community capital clusters. Hazard losses in military communities are highest near the Gulf of Mexico, Alaska, and the Dakotas. Select military communities in south Texas, New Mexico, and southern Alabama have above average levels of social vulnerability and hazard losses, and below average levels of resilience.

The results demonstrate that military communities' hazardousness is different from those of other communities in the United States and even within military communities based on the type of military base in those communities. Trends were not always consistent as unique findings occurred in the Hampton Roads region of Virginia and the Washington D.C metropolitan area. Some findings, such as those related to the importance of community capital to resilience, support the conclusions of research done at the community level and those at the individual and family level in military homes. The findings enable community leaders, state officials, and leaders in the Department of Defense to target critical areas that can reduce the hazardousness and improve military communities' resilience in the United States.

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CHAPTER 1

INTRODUCTION

Military installations are unique places in the landscape because they are fenced off and restrict access to a small percentage of the population but influence and impact the places around them. Military installations are self-governing and operate on many levels as independent cities, yet there are strong connections and links to the cities and communities outside their fences. Natural hazards do not observe the physical and political boundaries between military installations and local communities. Their negative impacts are felt on both places, often testing the relationship and connection between them. Military installations are sensitive to changes in the local community, and communities are sensitive to changes on the military installation. For example, many military installations rely on the local community for electric power generation and water treatment and are directly influenced by communities' policies regarding local development and land use along the borders (GAO, 2020). Local communities are likewise impacted economically and environmentally through the jobs and contracts a military installation provides, support for local school districts and services provided by DoD programs, and the military's use of the land and environmental pollution (Woodward, 2015). These connections often go unrecognized but are especially important to understand during times of crisis.

Military installations and local communities also face the same threats as other places in the United States, such as climate change and the increasing cost of disasters. The primary goal of this research is to understand the underlying conditions in "military communities," or communities heavily influenced by military installations, which may lead to different or unique disaster outcomes than other communities. By understanding the differences and unique characteristics in military communities' hazardousness, then policies and programs designed to reduce disaster risk can be optimized to meet the community's needs.

In 2019 the Department of Defense published a list of installations at risk to climate change in response to a congressional mandate. However, only recurrent flooding, drought, desertification, wildfires, and thawing permafrost were considered in the report (DoD, 2019a). The report was the first time the military published and recognized the impacts of climate-sensitive hazards on military installations. In the past, the DoD focused its efforts studying the impacts of climate change on military operations abroad, such as dealing with instability from a rising number of climate refugees in places like Africa and in the security of new shipping lanes opening in the Artic (Brzoska, 2012; U.S. Army War College, 2019). Although the recent identification of risks to hazards on military installations was long overdue, it failed to quantify the risk to hazards on these places. It also did not include any consideration of the impacts on the surrounding communities. This gap left local leaders in military communities, such as installation commanders and city managers, to work together to identify and mitigate their risk to hazards (McCollester, 2020). However, the current bottom-up approach lacks direction and standardization across the DoD, creating inefficiencies and knowledge gaps. Recently, the DoD has named climate change a threat to national security, which has accelerated the need to quantify and understand hazard impacts in military communities (DoD, 2021).

A communities' ability to respond and recover from hazards is largely dependent upon the underlying social vulnerability and resiliency of those places, as well as the amount of damage sustained during the event. Communities that require the most assistance in disasters are usually ones with higher social vulnerability, lower community resilience, and the most damage. However, these relationships are not linear and uniform (Cutter et al., 2014). Many factors in the community contribute to its social vulnerability and resilience to hazards, including the underlying socio-economic and demographic characteristics, social organizations, built environment, and others. Previous studies in hazards research have explored the differences in vulnerability and resiliency across the United States (Cutter et al., 2014). However, no research has identified differences in the vulnerability or resiliency between military communities and non-military communities, or the magnitude of damages as a result of hazards. Doing so will provide actionable evidence for military and community leaders to work together to reduce and mitigate negative disaster outcomes.

The method used to accomplish this will be to quantify and compare any differences in the social vulnerability and resiliency of military communities to non-military communities, as well as by the type of base that the community supports (Army, Navy, and Air Force). Hazard losses are also assessed to identify military communities that have sustained significant damage from past hazards, and whether those damages are different from other communities. Identifying any differences in these places can help policy and decision-makers focus resources and enact policies that benefit those communities. The following research questions are asked and used as a guide throughout the research:

Research Question (RQ) 1a: How do natural hazard losses compare between military communities and non-military communities?

RQ 1b: How do natural hazard losses compare within military communities by the type of military base (Army, Navy, Air Force)?

RQ 2a: How does the underlying social vulnerability compare between military and non-military communities?

RQ 2b: How does social vulnerability compare within military communities by the type of military base?

RQ 3a: How does the underlying community resiliency compare between military and non-military communities?

RQ 3b: How does community resiliency compare within military communities by the type of military base?

Chapter 2 discusses the existing literature related to military installations, natural hazard losses, social vulnerability, and community resiliency. Several gaps exist in the understanding of vulnerability and resiliency in military communities. Therefore, research is collected across disciplines and related to existing natural hazards research. Chapter 3 explains the data and methods used to answer the above research questions, including the statistical and spatial analysis. Chapter 4 describes and explains the results of the analysis. Finally, Chapter 5 discusses the implications of the results, other considerations in military communities, and future directions in the research of natural hazards and military geography.

CHAPTER 2

LITERATURE REVIEW

Researchers in geography, anthropology, economics, psychology, engineering, and others have published numerous studies on military bases, communities, natural hazards, social vulnerability, and resilience. However, each has a different perspective and focus but do relate to the primary themes of the thesis—social vulnerability hazard losses, and resilience. The literature is organized as an integrated review of the primary themes as follows. First, existing literature is reviewed identifying the traditionally view of militaries in civil-military relations and disaster response, and how military bases have been identified to influence the disaster cycle. Second, key concepts in social vulnerability are reviewed and how those relate to military geographies and military populations. Third, key concepts in community resiliency are reviewed and how those are related to military geographies and populations. Lastly, the geography of military bases and their hazardousness is reviewed, providing necessary background for following sections that have studied hazards and related concepts in areas with military bases.

2.1 TRADITIONAL APPROACH TO MILITARIES AND HAZARDS

The number of disasters, costs from damages, and deaths from climate-sensitive hazards have increased each decade since the 1970s (Smith and Katz, 2013). The military has played an increasing role in disaster response in the last few decades to assist overwhelmed local and state authorities. Known as "Defense to Civil Authorities" or DSCA, military response to hazards typically involves the states activating the National

Guard and occasionally active-duty troops for larger scale disasters. Local military bases and communities also sign local mutual aid agreements to assist one another during emergency response. The military has a plethora of resources on hand to aid local communities in response, such as high ground clearance vehicles, bulldozers, dump trucks, tents, cots, medical supplies, as well as doctors, power supply specialists, and soldiers (FEMA, 2011).

Most of the research on the military's role in disasters has been in political science, analyzing the civil-military relations and how state and local agencies work and interact with the military during disasters. Banks (2006) argues that disaster management in the United States has become more militarized, especially after Hurricane Katrina, due to the military's increased responsibilities in disaster response and FEMA's placement in the Department of Homeland Security. Malešič (2015) takes that argument further and urges caution on the military's increasing role in DSCA operations and the potential to degrade the separation of civil-military responsibilities and relations. He and others such as Ferris (2012) argue that militaries, civilian authorities, and humanitarian agencies should focus their efforts on planning and coordination in preparing for disasters so that civilian and military resources are efficient and reach their full potential. Others advocate for a more robust and flexible response from the military in disasters. Another critique in the military's response is that the traditional "respond to request" approach in DSCA operations is too slow and bureaucratic and should be a more flexible "sense-and-respond" approach, one that is approached from the bottom up (Embrey et al. 2010).

However, traditional civil-military research has left out how military bases work with and assist the local community from responding and recovering from disasters.

Ashcroft and Mason (2006) detailed the recovery of Keesler Air Force Base (AFB) after Hurricane Katrina. However, they did little to advance the understanding of how Keesler contributed to or diminished the response and recovery of nearby Biloxi, MS. Trivedi (2020) mentioned how local military units helped clear debris from schools in Biloxi but did not identify how Keesler AFB influenced the longer-term recovery of the area or the existing vulnerability and resiliency in the community. Because of their resources and funding sources, military bases are some of the first communities to recover after a natural hazard. They are used as staging grounds for FEMA, the Red Cross, and other government and non-government organizations (NGOs) (Navy Installations Command, 2021). Other research aimed at identifying the impacts of military bases on local communities has focused on the environmental damage and pollution that stems from military bases or left behind at closed sites (Davis et al., 2007). Economists have studied the impacts of military base closures through the Base Closure and Realignment Commission (BRAC) on local economies, which occurred after significant disasters in some situations (Hultquiest and Petras, 2012). There is a gap in research on how local military bases influence all aspects of the disaster cycle (preparedness, response, recovery, mitigation) in local communities. One aspect in which this research will address this gap is by advancing the understanding of how military bases and populations influence the community's underlying social vulnerability and resiliency to hazards.

2.2 VULNERABILITY TO NATURAL HAZARDS IN MILITARY COMMUNITIES

Vulnerability is a word that holds many different meanings depending on the context and discipline that is defining, measuring, and assessing it (Wisner, 2016). Vulnerability to natural hazards has two main dimensions, the human and physical dimensions (Fekete and Montz, 2017). Fekete and Montz describe the human dimension as being composed of susceptibilities and coping and adaptive capacities of people and social systems to hazards. This research investigates the human dimension of vulnerability, which is referred to as social vulnerability, and whether military communities possess unique susceptibilities and coping and adaptive capabilities. .

Social vulnerability to natural hazards is a topic thoroughly studied in recent years by social scientists. Social vulnerability is a concept that "identifies sensitive populations that may be less likely to respond to, cope with, and recover from a natural disaster" (Cutter and Finch, 2008, p. 2301). It is clear from past case studies and literature that hazards impact people differently, as people have different capacities to adapt from the physical, economic, and psychological impacts of hazards. Many of these differences have been identified through the socioeconomic and sociodemographic characteristics in communities (Cutter, 2003). Some of the characteristics that increase social vulnerability to hazards are a lack of wealth, dependency on care givers, less educated populations, renters, temporary and lower wage employment, female headed households, minority populations such as African American race and Hispanic ethnicity, and many others (Cutter, 2003).

The sociodemographic and socioeconomic characteristics are not determinants of vulnerability, but indicators for potential vulnerability. Hispanic populations, for example, are vulnerable to hazards because they may not speak English. This reduces their ability to understand and respond to potential hazards if the information is only delivered in English. However, this does not indicate that all Hispanic populations are vulnerable or that every Hispanic person is vulnerable. Some places with a majority of Spanish speakers, such as

Yuma, AZ, have emergency management programs and information readily available in English and Spanish. Other places, such as Grand Forks, ND, do not, potentially making the same information more difficult to access for Spanish speakers. Other characteristics, such as age (elderly and young children), are dependent on others for care and resources when responding to natural hazards and is valid across geographies. Many other indicators of social vulnerability have been identified by researchers (Appendix A).

The demographic characteristics of military families, which are slightly different from civilian counterparts, also contribute to military communities' social vulnerability. Military families are slightly more African American and have slightly less Hispanic ethnicity than the general population (Clever and Segal, 2013). They also have more educational attainment (at least high school diploma) than the general population due to enlistment requirements and benefits to service members (ibid.). Clever and Segal (2013) and Harrel (2000) noted several challenges unique to military families: frequent moves, prolonged and unpredictable working hours, deployments, and the prevalence of mental and physical health ailments in veterans. Some of these challenges increase the social vulnerability in military communities. Frequent moves, for example, lead to higher percentages of renters in military communities. Renters are considered more socially vulnerable because they have little control over repairs to damaged properties (Morrow, 1999). An outcome of mental and physical health ailments is homelessness, which is an indicator for vulnerability. Veteran homelessness has been identified as a growing problem in the United States, especially in communities with military bases (Villafan, 2016). Others characteristics in military families decrease their social vulnerability to hazards. These include higher levels of educational attainment, stable federal employment opportunities, higher incomes of service members, and healthcare availability through Tricare insurance (Clever and Segal, 2013).

Qualitative studies that identify socially vulnerable characteristics through interviews, surveys, and field work form the basis for many quantitative social vulnerability measures. While most case studies with qualitative findings are neither comparable across geographies nor by hazard type, quantitative measures of vulnerability can be compared to different places. Quantitative variables are identified and used as proxies to measure the indicators of vulnerability. Variables that are selected are scaled using various normalization techniques, such as z-score and linear min-max so that are relative to each other. The variables are then separated into like factors of vulnerability using a hierarchical, deductive, or inductive approach (Tate, 2012). Inductive methods involve using principal component analysis or similar statistical techniques to reduce the number of variables into factors that explain the most variance in the data. Deductive or hierarchical methods involve delineating variables into predetermined factors based on the similarity of the variables (ibid.). Regardless of the method, factors of vulnerability are then combined using an additive or weighted approach to form a composite index of vulnerability which can be compared across geographies.

2.3 COMMUNITY RESILIENCE OF MILITARY COMMUNITIES

Resiliency is another term where the meaning and context of the word are often ambiguous or conflated. Common descriptions of resilience in hazards research and other fields include bounce-back, absorbing, preparing and planning, recovering from, and adapting to adverse events (Emrich and Tobin, 2017). Vulnerability and resilience are sometimes confused as the same concept or opposing concepts, but as shown in Cutter et al. (2014) they are not the same. The term resilience in this research is identified more as absorbing, recovering, and adapting to natural hazards. Vulnerability is viewed more as the susceptibility to experiencing the negative impacts of natural hazards.

Resilience in communities is composed of the capacity of both individuals and the greater community to bounce back and forward after disasters. These capacities are separated into distinct concepts, known as capitals or domains of resilience. Nguyen and Akerkar (2020) identified six capitals most likely to represent resilience in existing literature covering the subject. The six capitals they identify are social, physical, community, individual, economic, and ecological, while other authors replace individual with others like institutional, and include individual capacities within the social domain (Cutter, 2014). While the names of the domain may differ, many of the indicators and characteristics within those domains are the same.

Indicators for resilience within these domains includes both socioeconomic characteristics such as wealth and income equality, and place based characteristics such as the transportation access in the community. Other examples of indicators that are within the six domains of resilience include how prepared and experienced the community is responding to hazards, the healthcare and hospital capacities relative to the population size, the political and religious engagement in the community, the diversification of the local economy, and many others (Cutter et al. 2010). Engagement in community level organizations, such as religious or civic groups, is identified in several case studies as increasing resilience (Murphy, 2007). Other studies have shown that a diversified economy is important for communities, so that if one employer or sector leaves the community, other sectors and employers are available to meet demand (Adger, 2000). Appendix B identifies other characteristics that were found in case studies to be indicators of resilience and separates them by domain.

There are unique characteristics in military communities that may influence their overall resilience. Community capital in military communities is one of the domains that may be influenced negatively by military populations. Military families are transplants from other communities in the U.S, which decreases their attachment to places and the number of networks and connections in the community. Although research has yet to identify the relationship between military populations and lower levels of resilience at the community level, studies conducted by psychologists, family life practitioners, and others in the behavioral sciences have studied the importance of engagement in local communities at the individual and family level. Mancini et al. (2018) identified a positive relationship between military families' resilience and the number of connections made to organizations in local communities outside military installations. Likewise, Huebner et al. (2009) identified positive impacts to military families that built and maintained relationships in the community.

Other domains, such as environmental, may have both positive and negative influences on resilience in military communities. Military bases have large areas of natural vegetation that are used as training areas for unit training and weapon testing. On one hand, training areas act as natural buffers and are preserved as undeveloped areas. Undeveloped areas generally improve the flood capacity of watersheds because the water is absorbed by the soil and natural vegetation, and wetlands and riparian areas act as buffers. On the other hand, training areas may have dangerous unexploded ordinance or areas of heavy metal contamination, which can leach into the water supply (Davis et al. 2007). Military bases also store and keep large quantities of fuel, chemicals, and other toxic chemicals that can spill and negatively impact the environment and community.

Community resilience is measured using similar methods as those mentioned for social vulnerability. Proxy variables are identified as quantitative measures for capitals of resilience, and then normalized to like scales. The variables are placed into capitals of resilience, mostly using a hierarchical or deductive approach, where they attempt to measure that concept of resilience (economic variables fit into economic capital, for example). The final composite index is the additive or weighted combination of those capitals. Community leaders, state level organizations, and others can then use the final values or the individual capitals to compare the resilience between places, and use it as a tool to aid in decision making and for allocating resources.

2.4 HAZARDOUSNESS OF MILITARY COMMUNITIES

In the late 1700s and early 1800s, bases were established along the Gulf and Atlantic coasts to protect ports and cities from bombardment and blockades from foreign navies (Floyd, 1997). In the 1800s, bases such as Fort Riley, KS and Fort Bliss, TX were established along transportation corridors in the western frontier and southern border to protect pioneers and settlers moving into those areas (Doe III, 2010). Further expansion of bases before and during the World Wars led to the military establishing large military bases in the West to test new equipment and weaponry, such as tanks and nuclear bombs (Balbach, 2014). Land in the west was cheap, and small towns sprung up in primarily rural areas outside of the base to support it. This pattern was replicated throughout the west.

Other bases built or expanded during the World Wars were established in more populated coastal areas, along intercoastal waterways, and directly on the shoreline and barrier islands, such as Coronado Naval Air Station, CA and Eglin Air Force Base, FL. The coastal locations gave them easy access to ports and the ocean, where they can project power to other parts of the world. However, bases located in coastal areas leave them in extremely vulnerable locations to natural hazards, where tidal flooding, storm surge, and hurricanes cause billions of dollars in damage to military equipment and infrastructure (NDAA, 2020). Yet, even continental bases experience damage from other hazards like annual flooding events, wildfires, tornadoes, or severe storms. Significant damage at military bases in the last three years has occurred from a diverse range of hazards such as Hurricane Michael, Hurricane Florence, the Platte and Missouri River floods of 2019, the 2018 hailstorms in Colorado, and an EF-3 tornado at Naval Submarine Base Kings Bay (NOAA, 2019).

Losses from hazards on military bases are not always visible to the public. Only thorough the annual National Defense Authorization Act (NDAA) and supplemental disaster appropriations are military construction spending from hazard damages available to the public. For example, additional appropriations to the Disaster Relief Act in 2019 allocated over $1.1 billion in military construction to rebuild Tyndall Air Force Base after Hurricane Michael, and the 2020 NDAA allocated an additional $1.5 billion in military construction required to rebuild the hangars and facilities that were destroyed (NDAA, 2020). However, hazard losses in the surrounding communities of Bay County, FL and Panama City are available from public sources, such as the National Weather Service and U.S. Geological Survey. Other databases, such as the Spatial Hazard Events and Losses Database in the United States (SHELDUS) aggregates loss data from those sources to form a more complete picture of the total damages from hazards (CEMHS, 2020).

Increasing losses and the vulnerability of many coastal military bases to climate sensitive hazards has not gone unnoticed by military departments in the DoD. The DoD conducted site specific studies related to infrastructure vulnerability at Naval Base Norfolk, VA and Coronado Naval Base, CA to sea level rise (SERDP, 2017). However, most of the research done by the DoD has been hazard specific and focused on the physical vulnerability of existing infrastructure to hazards. Although this research doesn't attempt to replace site specific hazard assessments, it does advocate for a wider approach in understanding the hazardousness of military communities. This can be accomplished by incorporating not only the military base but local community. Hazard losses from sources such as SHELDUS can be combined with indices of vulnerability and resilience to explore the hazardousness of places (Tate et al. 2010; Emrich and Cutter, 2011; Borden and Cutter, 2008).

2.5 CONCLUSION

Hazard losses, social vulnerability, and resilience are explored to understand the hazardousness of military communities. Quantitative measures of social vulnerability, community resilience, and hazard losses in military communities are compared to non-military communities, including the components that create the overall indices of vulnerability and resilience. The research questions are relatively broad in scope and approach the problem from the top down. This approach is not an attempt to replace local hazard assessments in military communities that identify the specific hazard threats and vulnerabilities in detail. However, this thesis will help bridge the gap in understanding how military populations and military bases influence local communities' existing vulnerability and resiliency to hazards, which is missing in existing literature.

CHAPTER 3

DATA AND METHODOLOGIES

The study area includes all 50 states to account for all hazard types and a vast geographic extent. Analyses were conducted at the county level to mirror the scale of the input data. Any level higher than the county, such as the state, does not provide the necessary detail to perform the analysis required to differentiate between the factors driving the vulnerability and resiliency of military communities. Any level below the county is outside the scope of this research and better suited when analyzing smaller geographic regions, individual states, or when the data is available at those levels. Also, emergency management and decision makers that influence hazard mitigation funds and other resources are consolidated at the county level in most areas of the US (Sherrieb et al., 2010).

3.1 DATA SOURCES

Data were collected from four sources, including the Department of Defense (DoD), the United States Census Bureau, the Hazards and Vulnerability Research Institute at the University of South Carolina (HVRI), and the Center of Emergency Management and Homeland Security at Arizona State University (CEMHS). Military installation, ranges, and training areas (MIRTA) shapefiles were downloaded from the US Army Corps of Engineers data repository available to the public (DoD, 2017). The 2020 MIRTA dataset includes the name of the military base, the service branch (Army, Navy, Air Force, etc.), the bases' status (active, reserve, national guard), and the spatial boundary. County boundary shapefiles were downloaded from the United States Census Bureau and provided the basis for joining non-spatial data into the GIS interface (Census, 2020). Data tables for military employment and insurance data were also downloaded from the US Census, which is expanded on in the following section.

The Social Vulnerability Index (SoVI) is used as the measure of social vulnerability and was downloaded from HVRI. While many indices exist to measure the concept, including a freely available social vulnerability index (SVI) from the Center for Disease Control, SoVI is one of the most widely cited and used social vulnerability index in academia, state governments, non-profits and NGOs, and even the federal government. SoVI also performed better than SVI in attempts to validate the indices using disaster outcomes (Rufat et al., 2019) and SoVI displayed reliable results at different scales through sensitivity analysis (Schmidtlein et al. 2008). The Corps of Engineers uses SoVI methods to identify environmental justice impacts for flood control projects and the Federal Emergency Management Agency (FEMA) has adopted SoVI in their recent Hazard Risk Index tool (Dunning and Durden, 2011; FEMA, 2020).

Using principal component analysis, SoVI reduces an extensive range of socioeconomic variables known to influence the vulnerability of places into eight factors that explain the most variance in the data (Cutter et al. 2003). The SoVI used in this analysis was not calculated by the author but used with permission from HVRI, which was composed using the 2014-2018 ACS 5-year estimate. The eight factors of social vulnerability in the dataset are race (African American and social status), wealth (low), age dependence, ethnicity (Hispanic and education), special needs populations, race (Native

American), service sector employment, and gender (Female). Cutter et al. (2003) describes the framework behind SoVI and a more detailed description of how the index is calculated.

Similar to social vulnerability, many indices exist that attempt to measure community resilience. The Baseline Resilience Indicators for Communities (BRIC) is used in this research because it is one of the few indices available for all 3,143 counties in the US and was developed using a multi-hazard approach (Ostadtaghizadeh, 2015). BRIC is also widely used in the hazards and emergency management community, evidenced from its inclusion in the National Risk Index with SoVI (FEMA, 2020).

BRIC follows a different approach than SoVI's inductive method using principal component analysis. BRIC uses a deductive approach that starts with six capitals representing the different types of resilience in communities. Forty-nine total variables were identified and then placed into their six corresponding capitals of resilience based on expert knowledge and previous literature (Cutter et al., 2014). Each capital of resilience has a theoretical range of 0-1, and then added together to create a composite index with a theoretical range of 0-6. The six capitals of resilience in BRIC are social, economic, institutional, infrastructural, environmental, and community capital. BRIC capital values and overall scores were downloaded with permission by HVRI and compiled using various data sources collected from 2010-2016.

Hazard loss data was obtained from SHELDUS, which is maintained by the CEMHS at Arizona State University (CEMHS, 2020). Data was downloaded for all counties in the U.S. from the years 1960-2018, and for all hazards. SHELDUS includes hazard loss data for crop and property losses from 17 different hazards types, including meteorological events such as drought and hail, and geophysical events such as earthquakes and tsunamis. Crop and property losses were adjusted for inflation into 2018 dollars and standardized per capita using 2018 population totals for each county from SHELDUS. Likewise, losses were standardized per capita so that values could be compared between less populated rural areas and more populated urban areas. Property and crop losses were then summed to get total hazard losses per capita from 1960-2018.

SHELDUS does have limitations, such as only providing direct losses from natural hazards and not indirect losses, such as decreased economic activity (Hahn, 2017). Scale is another limitation of SHELDUS, which aggregates data to the county level, making it difficult to understand the hazard exposure at the local level (Emrich and Cutter, 2011). Despite these limitations, however, SHELDUS presents the best available database for natural hazard losses in the United States due to its complete coverage of the United States and long record of loss data going back to 1960. Table 3.1 provides descriptive statistics on hazard losses, SoVI values, and BRIC values used in the analysis.

Table 3.1. Descriptive Statistics for Hazard Losses, SoVI, and BRIC (n = 3,143 counties)

	Total Damages Per Capita	**SoVI Score**	**BRIC Score**
Mean	$11,354	0	2.729
Median	$3,877	.03	2.733
Std. Deviation	$34,676	2.89	.147
Range	$1,248,308	25.6	1.174
Kurtosis	563	2.12	.335
Skewness	18.9	.367	-.283
Kolmogorov-Smirnov Test for Normality	Fail (p = .000)	Fail (p = .000)	Fail (p = .000)

3.2 DEFINING MILITARY COMMUNITIES

In this research, the term community is synonymous with a county. Although a community is more likely to be used colloquially as a neighborhood or smaller census unit such as census tract, the term is used more broadly in this research to describe places significantly influenced by military installations and military populations. This is primarily due to the level of analysis conducted at the county level and because military installations are often large and cross county boundaries. Military members and families are not constrained to only living on the military base and work, live, and go to school in the community. The military community is also sometimes used to describe the people that are in the military or their family members (DoD, 2019b). However, here it is referenced as a place, which includes the people in the military, civilians, the organizations, networks, and all other components and relationships that make up a community. Two census variables, using the 2014-2018 5-year American Community Survey estimates, are used in combination as a proxy to identify military communities, as well as the Military Installation, Ranges, and Training Areas (MIRTA) shapefile from the Department of Defense (U.S. Census, 2019; DoD, 2017). The number of people with Tricare Insurance (table C27008) and the number of people with military employment (table B23001) is used as a pass or fail screen to identify potential military communities. The MIRTA shapefile was used as a final screen to ensure only counties near an active military base were considered military communities.

Tricare Insurance is the insurance program for the military and their family members. Eligibility for Tricare extends to the national guard, reserves, military retirees (20+ years of service), and Coast Guard. The additional dataset of active-duty employment helped pinpoint communities with a significant military presence rather than places with reservists only, for example. Tricare insurance and military employment variables were normalized as a percent of the population. The distribution of the percent of the US population with Tricare insurance or active-duty employment was highly skewed, with most counties having only a small percentage of people with those characteristics. Again, this paper defined military communities as counties with significant influence by military populations and bases, which prior research has not identified. Therefore, a subjective determination for thresholds in Tricare insurance and military employment data was made after close inspection of the descriptive statistics, distribution, research into individual counties, and the author's best judgment based on experience.

Table 3.2 displays the descriptive statistics for the variables used to identify military communities, the cutoff criteria, and the purpose of the variable. Counties with more than 4.5% of the population with Tricare insurance and 1.5% of the population with military employment were determined to be considered military communities. The ratio of Tricare to military employment equates to a 3:1 ratio, which is close to the 2:1 ratio of military family members to active-duty soldiers in the U.S (DoD, 2019b). The additional unit accounts for other populations eligible for Tricare and live in military communities (retirees, reservists). Lastly, counties without an active-duty military base or were not adjacent to a county with an active base were screened out using GIS. The geographic criteria helped identify only counties near an active-duty military base, where their influence is more significant. The geospatial criteria screened out five counties. Two of the five had Coast Guard bases (Kodiak Island, AK and Pasquotank County, NC), two were rural counties tangentially influenced by Fort Riley (Clay and Pottawatomie Counties, KS), and one was a reserve base outside of New Orleans (Plaquemines Parish, LA).

Table 3.2. Descriptive statistics and criteria for classifying military communities.

Variable	Mean	Median	Skew-ness	Military Community Criteria/Cut-off	Purpose
% Tricare Insurance	2.88	2.13	6.23	~ 90th percentile (4.5%)	Identify people connected to military service (includes military dependents, retirees, reserves, national guard and coast guard)
% Active Military Employment	.287	.033	17.5	~ 95th percentile (1.5%)	Identify active duty service members
Location of Military Base				County contains an active military base or is adjacent to a county that contains an active base	Identify counties that are geographically influenced by an active military base (screen out Reservist, National Guard, Retiree, etc.)

Upon close inspection of the counties that passed all thresholds, the criteria did well in representing the 106 communities heavily influenced by military bases and populations. This was determined based on the author's personal knowledge and expert judgment of military installations and communities. Among some of the more notable counties classified as military were large counties like San Diego, CA and Honolulu, HI, medium-sized counties of El Paso, TX and El Paso, CO, and smaller counties and independent cities such as Petersburg, VA, and Alexandria, VA. Bexar County, TX, which is often thought of as a military community, was screened out. Bexar County, Texas is home to Joint Base San Antonio, which has several military facilities in the county. However, military members are a small percentage of the overall population (1.07% military employment) compared to other large counties like San Diego, California (2.76% military employment). Counties that met all three criteria were classified as military communities (N=106), while the remaining 3,037 were classified as non-military communities. Figure 3.1 displays the counties classified as military and non-military, with clusters in the Hampton Roads region of Virginia, the South, and a smaller number of counties scattered throughout the West and Midwest.

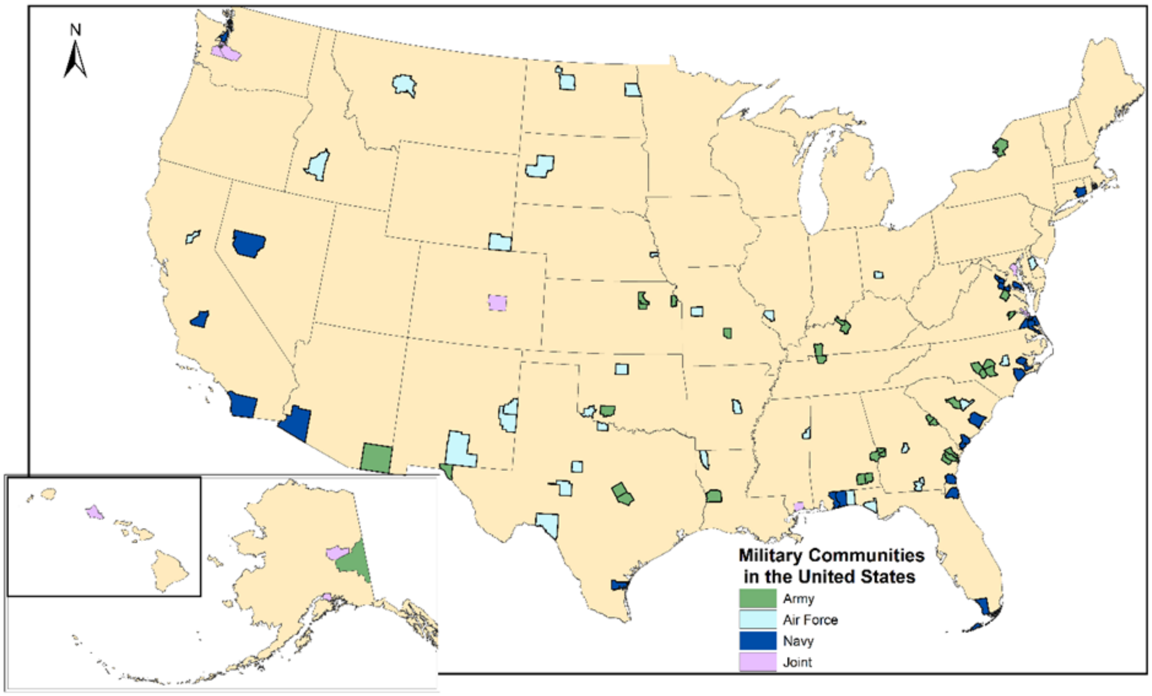

Figure 3.1: Military Communities in the United States differentiated by service branch (non-military communities in beige color).

To answer the second part of the research questions, the type of military base in the community was identified and classified either as Army, Air Force, Navy, or Joint. Joint communities were those with a combination of military installations belonging to multiple branches of the military. For example, El Paso County, CO, was defined as a Joint community because it is home to Fort Carson (Army) and several Air Force Bases (AFB) such as Peterson AFB and Schriever AFB. Communities with only one type of military base were classified under that type of base. Marine Corps bases were classified as Navy due to being under the Department of the Navy's jurisdiction, and Space Force garrisons are classified as Air Force. As a result, 13 communities were classified as Joint, 28 as Navy, 31 as Air Force, and 34 as Army.

3.3 STATISTICAL ANALYSIS

A variety of statistical tests, spatial statistics, and mapping techniques answer the research questions and determine differences between hazard losses, SoVI, and BRIC in military and non-military communities. Hazard losses were normalized on a per capita basis to account for urban and rural differences and adjusted into 2018 dollars to account for inflation over time. Property and crop losses were summed for all counties during the 59 years of 1960-2018 to get the total damages used in the analysis. Although the number of service members and the overall population in military communities have changed over time, the complete dataset in SHELDUS (59 years) was used to capture as many hazard events as possible so as to not skew data towards more recent events.

All three variables of total hazard losses, SoVI, and BRIC exhibited non-normal properties and failed the Kolmogorov-Smirnov test for normality (Table 3.2). Due to failing the normality assumption and the significant difference in the number of non-military communities and military communities, non-parametric statistical tests were conducted. The Mann-Whitney U test was conducted to identify significant differences between the mean ranks of the three variables (Hazard losses, SoVI, BRIC) in military and non-military communities. The Mann-Whitney U test ranks all communities from 1 to 3,143 based on the value of the variable, and determines statistical significance between those ranks. The community with the lowest total hazard losses per capita would rank as 1, while the community with the highest losses ranks as 3,143, for example. This negates the influence of extreme outliers on the mean values and other non-normal characteristics in the data. The Kruskal-Wallis test was conducted to understand the differences in the variables by type of military community (Army, Air Force, Navy). This method also tested differences in the mean ranks of the variables.

Next, the factors of SoVI and BRIC capitals were analyzed further using binary logistic regression (between military and non-military communities) and multinomial logistic regression (between types of military communities). The choice of binary logistic regression was similar to Cutter et al. (2016), which explored the capitals of BRIC between rural and urban communities. The beta coefficient, Wald statistic, and odds ratio for each of the significant contributing variables in the models determined the driving factors in differences of social vulnerability and resilience between military and non-military communities. Before conducting the logistic regression analysis, however, SoVI factors and BRIC capitals were standardized using z-scores to account for any outliers that may influence the model. Also, to account for the large disparity in the number of communities in each category, 106 military and 3,037 non-military, a random sample of 106 non-military communities was taken before conducting the regression models[1]. Additionally, a random sample of 28 Army and 28 Air Force communities was taken to account for sample size differences before conducting the multinomial regression model (only 28 Navy communities in the dataset). All statistical analyses were completed using SPSS Version 26 (IBM Corp, 2020).

[1] Binary logistic regression models did poorly when all counties were included in the model. Therefore, a random sample of 106 non-military counties were selected in the regression analysis. To remain consistent, 28 Army and Air Force counties were randomly selected so that the number of counties for each category (Army, Air Force, Navy) were the same.

3.4 SPATIAL ANALYSIS

To fully understand the significant differences and drivers of social vulnerability and community resilience in military communities, the community's location must also be considered. Social vulnerability and community resilience in the United States have high and significant levels of spatial autocorrelation (p = .000) with distinct clusters in some areas of the United States. Spatial autocorrelation violates the assumption that observations in the data are independent of one another, which was not addressed in the logit models directly. Therefore, Anselin Local Moran's I was employed as a form of sensitivity analysis to determine if the logit models' results were due to the community's location and existing geographic trends or were unique to military communities irrespective of location. Anselin Local Moran's I is a technique used to identify statistically significant outliers in geographic clusters of areas with high or low values (Anselin, 1995). It is a local indicator of spatial association (LISA statistic) and provides four outputs, clusters of high values, clusters of low values, high-value outliers in low clusters, and low-value outliers in high clusters (ESRI, 2020). Communities that do not exhibit the same values as those around them were reported as statistically significant outliers, which was essential in understanding the differences between places. Special attention was given to military communities identified as outliers to describe and analyze any patterns in the results. Hawaii and Alaska were excluded from the spatial analysis because of the contiguity requirement in using the county boundary polygons. Spatial statistics and maps used ESRI Arc Map 10.7.

In addition to mapping and evaluating outliers, the binary and multinomial regression models' residuals were visually inspected for spatial patterns. Visual inspection instead of spatial statistics was performed because the binary and multinomial models only included 212 and 84 counties, respectively. Visual inspection of the residuals further helped understand the driving factors in vulnerability and resiliency, where communities with high residuals were those that the regression models had trouble in classifying correctly, indicating different influencing variables. The perspective given through the spatial analysis, combined with the statistical evidence and hazard loss data, enabled a better understanding of the threat and risk that hazards place on those communities. Results are presented in four parts; first identifying the differences between military and non-military communities, then analyzing only military communities by type, next by analyzing hazard losses combined with the underlying conditions in places, and finally, a summary of the results.

CHAPTER 4

RESULTS

The first half of the results section identifies differences between military communities and non-military communities, while the second half identifies differences in military communities based on the type of military base in the community. In both comparisons, results from descriptive and inferential statistics are presented first, followed by the spatial statistics. Lastly, hazard losses in military communities are explored in more detail, and put into context with the results from analyzing social vulnerability and community resiliency.

4.1 COMPARING MILITARY AND NON-MILITARY COMMUNITIES

Differences in the levels of hazard losses and social vulnerability between military and non-military communities in the United States were found to be statistically significant. Although there were differences in community resilience levels, those differences were not significant based on the Mann-Whitney *U* test. Table 4.1 displays the mean values, mean ranks, the standardized test statistic, and *p*-value when tested at the 95% confidence level. Hazard losses and social vulnerability were significantly lower in military communities than in non-military communities, and resiliency was higher in military communities. However, the difference in resiliency was not statistically significant. The composite SoVI scores need to be unpacked and analyzed further through statistical and spatial analysis to understand why military communities were less socially vulnerable.

Table 4.1. Comparing Military and Non-Military Communities

	Community Type	Mean	Mean Rank	Standardized *U* Statistic*	*p*-value
Total Hazard Losses	Military Non-Military	\$6,740 \$11,515	1,198 1,584	-3.443	.000
SoVI	Military Non-Military	-1.295 0.045	1,158 1,585	-4.767	.000
BRIC	Military Non-Military	2.738 2.729	1,652 1,568	.938	.350

*Negative sign direction indicates association with military communities; n = 106 for military communities and 3,037 for non-military communities

4.2 DIFFERENCES IN SOVI FACTORS BETWEEN MILITARY AND NON-MILITARY COMMUNITIES

Through binary logistic regression, social vulnerability factors that associate more with military communities than non-military communities were identified to help understand the drivers behind their lower SoVI scores. Again, the eight factors that comprised the social vulnerability index were wealth (low), race (African American) and social status, age (elderly), ethnicity (Hispanic) and lack of health insurance, special needs populations, service sector employment, race (Native American), and gender (Female). The logit model was statistically significant ($\chi^2(8) = 120, \mathrm{p}$ =.000) and t Table 4.2 displays the beta coefficient (B), Wald statistic, significance levels, and odds ratios for each variable in the model. Age and special needs factors stand out in explaining the differences between military communities and non-military communities.

In logistic regression, the odds ratio was interpreted as the number of times more likely to be associated with a category (dependent variable) considering a one-unit increase in the factor (independent variable) (Bewick et al., 2005). Therefore, after interpreting the results, communities were 6 and 7 times more likely to classify as non-military with every one-unit increase in the age and special needs factor scores, respectively. Military communities had a lower median age and fewer social security beneficiaries, which were variables in the age factor. Likewise, non-military communities had a larger percent of nursing home residents and hospitals per capita (special needs factor). Communities were also one and a half times more likely to classify as non-military with a one-unit increase in wealth (low). Military communities had higher amounts of wealth than non-military communities, and some of the variables included in this factor were median income, median home value, and median rent.

Other variables that significantly contributed to the model were service sector employment and race (African American and social status). These factors were two times more likely to be associated with military communities considering a one-unit increase in the factor scores. Variables in these factors included service sector employment and female participation in the workforce (service sector), and African American and female-headed households (race and social status). Ethnicity (Hispanic), race (Native American), and gender (female) were not significant contributors to the model.

Table 4.2 Binary logistic regression results with factors of SoVI presented in descending order based on the Wald statistic.

SoVI Factor	***B***	**Wald χ^2**	***p*-value**	**Odds ratio**	**Likely category with one unit increase**
Age	-1.80	40.94	.000	6.02*	Non-military
Special Needs	-1.98	18.89	.000	7.25*	Non-military
Wealth (low)	-0.50	12.68	.000	1.65*	Non-military
Service Sector Employ.	0.88	10.86	.001	2.40	Military
Race (African Am. and Social Status)	0.70	8.13	.004	2.03	Military
Ethnicity (Hispanic)	-0.26	1.73	.189	1.25*	Non-military
Race (Native American)	0.20	0.53	.466	1.22	Military
Gender (Female)	0.08	0.13	.723	1.08	Military

*Inverted Odds Ratios; Negative Beta coefficients denote associations with non-military communities, positive coefficients denote associations with military communities.

When the communities classified incorrectly by the model (high residuals) were examined, the driving factors of social vulnerability in military communities was further highlighted. Higher age vulnerability and lower race (African American and social status) vulnerability were noticed in the 17 military communities that the model incorrectly classified as non-military. The three counties with the highest residuals were military communities with large populations of retirees (high age factor score). Monroe County, FL, Moore County, NC, and Beaufort County, SC are prominent retirement communities (Florida Keys, Pinehurst, and Hilton Head, respectively) and have military bases in the counties. Other counties with high residuals had a lower race and social status factor score and are located in the upper Great Plains and Alaska. These counties were Meade County, SD, Ward County, ND, and Southeast Fairbanks, AK. No other spatial trends were visually identified in the residuals. Counties with high residuals highlight that not all military communities are alike and that broad, generalized observations should be used with caution.

The driving factors of social vulnerability in military communities were quite consistent, especially in communities dominated by military employment (Table 4.3). Chattahoochee County, GA, Pulaski County, MO, Onslow County, NC, Geary County, KS, and Christian County, KY all have the highest percentages of military employment in the United States and service sector employment is the leading factor of social vulnerability in each of those counties. Service sector employment was high because military bases generate and require many service sector positions such as teachers, nurses, maintenance, cashiers, and human resource professionals, to name a few. They also generate service positions outside the base that cater to military members and families, such as retail and banking. Military spouses also fill these positions, increasing female participation in the workforce which further increases service sector employment factor scores. However, communities dominated by military employment have relatively lower overall SoVI scores than other communities in the United States, driven by low age and gender factor scores. Small changes to the military bases in these communities, whether from troop level reductions or damages and impacts from natural hazards, are likely to have outsized negative impacts in the community due to their reliance on military spending and lower wage and hourly service sector opportunities.

Table 4.3. Counties with highest percent military employment and their SoVI factor scores.

County	Percent Military Employ.	SoVI Factors*							
		1	2	3	4	5	6	7	8
Chattahoo-chee, GA	52	0.40	-0.58	-3.53	-0.86	1.11	0.12	1.46	-6.21
Pulaski, MO	28	-0.49	0.16	-2.22	-0.40	-0.14	0.20	1.87	-3.07
Onslow, NC	25	-0.18	0.03	-1.99	-0.55	-0.29	0.07	1.94	-2.20
Geary, KS	22	-0.28	-0.26	-1.98	-0.20	0.58	0.20	2.72	-1.30
Christian, KY	14	0.61	0.18	-1.62	-0.33	0.56	0.07	1.62	-1.21
Vernon Parish, LA	14	0.28	-0.03	-1.31	-0.29	0.19	0.22	0.43	-1.86
Coryell, TX	14	-0.12	0.42	-1.84	0.07	-0.70	-0.20	1.53	-0.62
Norfolk, VA	12	1.58	-1.04	-1.80	-0.41	0.75	0.30	1.45	-0.71
Liberty, GA	12	1.26	-0.35	-1.59	-0.21	0.17	0.24	1.39	-0.58
Elmore, ID	12	-0.56	0.11	-0.97	0.40	-0.18	0.48	0.38	-0.97

*Factor 1 = Race (African American and Social Status); Factor 2 = Wealth (low); Factor 3 = Age; Factor 4 = Ethnicity (Hispanic); Factor 5 = Special Needs Populations; Factor 6 = Race (Native American); Factor 7 = Service Sector Employment; Factor 8 = Gender (female).

4.3 SPATIAL ANALYSIS OF SOCIAL VULNERABILITY IN MILITARY COMMUNITIES

ArcMap 10.7 was used to identify clusters of high and low SoVI values, as well as associated outliers using Anselin Local Moran's I. Outliers, were important to identify because they denote reversals in geographic trends. Suppose military communities are consistently among outliers in high-value clusters located throughout the US. In that case, it can be assumed that characteristics unique to military communities drive the lower values in those clusters rather than prevailing demographic and socio-economic trends of the area.

High-value clusters of social vulnerability were found in the Great Plains stretching south into Texas, as far west as Arizona, and as far east as Mississippi (Figure 4.1). Pockets of high social vulnerability clusters appeared in small areas of the Carolinas and South Florida. Among the ten military communities with the highest SoVI values, seven were in Texas, Arizona, and New Mexico, and no military communities in those states were low SoVI outliers. Hispanic ethnicity and service sector employment were the two leading factors in all seven of those communities (El Paso, Val Verde, and Kleberg Counties in Texas, Yuma and Cochise Counties in Arizona, and Roosevelt and Curry Counties in New Mexico). Although military communities have lower SoVI values overall, only 4 of the 18 (22%) military communities located in high-value clusters were low-value outliers. Those communities were Meade County, SD, Lonoke County, AR, Bossier Parish, LA, and Onslow County, NC. The four counties all have high percentages of the population using Tricare Insurance (greater than 10%), but were not spatially concentrated in any area.

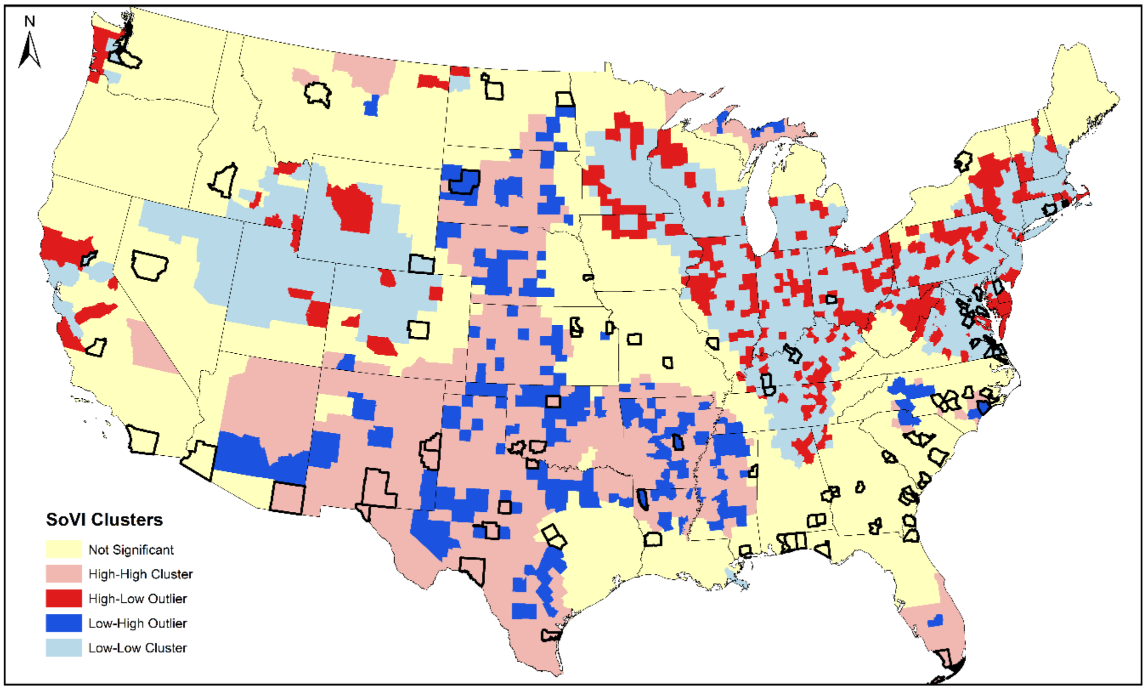

Figure 4.1: Anselin Local Moran's I output of SoVI values (military communities in dark outline).

Low-value clusters of SoVI were located in the Mountain West and the Northeast stretching into the Midwest. Nine out of the ten military communities with the lowest SoVI values were located in low-value clusters. These communities generally have low age, wealth, and service sector employment vulnerabilities compared to other military communities. Interestingly, 5 of 28 (18%) military communities in low SoVI clusters were outliers of high social vulnerability and geographically clustered in southeast Virginia. The high number of outliers was an unexpected result, given that military communities have lower SoVI scores than others. These five outliers of high social vulnerability were located in the Hampton Roads region and nearby Petersburg, VA. In this area of Virginia, counties are smaller in size and often operate as independent cities. The differences in social vulnerability levels between communities that are close in geography are notable and stark. The five communities of Petersburg, Newport News, Hampton, Norfolk, and Portsmouth have significantly lower social vulnerability than their six neighboring military communities (Figure 4.2).

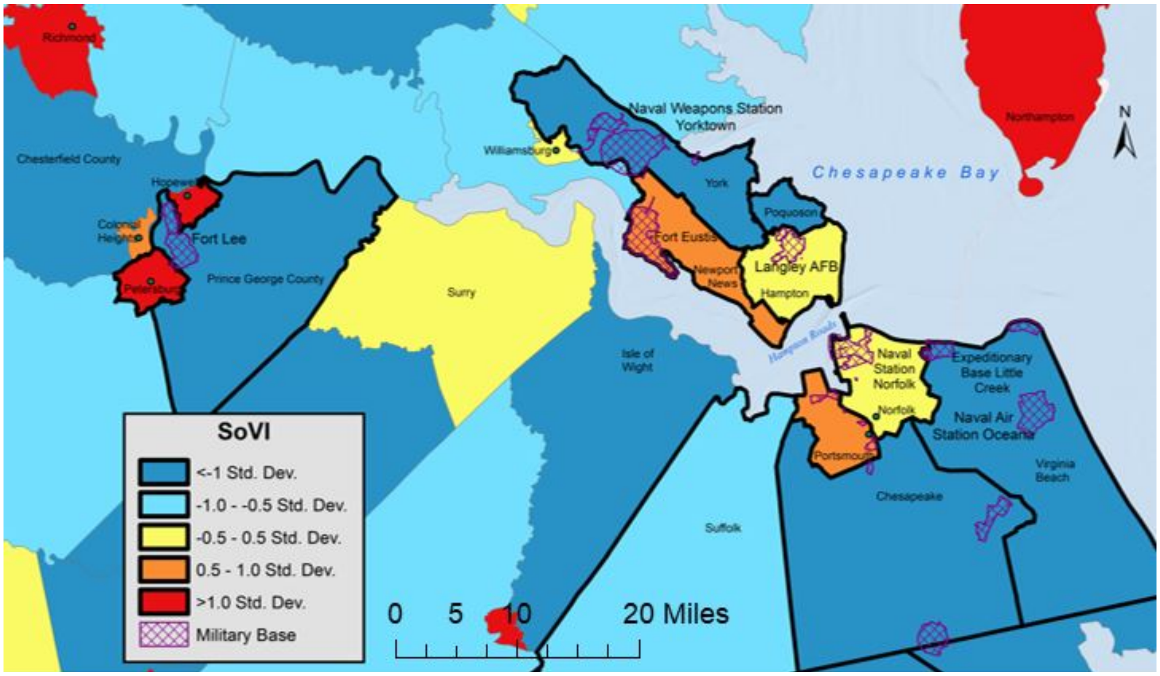

Figure 4.2: SoVI by county in the Hampton Roads region of Virginia (military communities in dark outline).

North of the Hampton Roads (water feature) is Poquoson, York, Hampton, and Newport News. These communities are Joint communities, as there is a combination of Army, Air Force, and Navy bases nearby. Poquoson and York are primarily non-Hispanic white and wealthy communities with military bases located within their borders. These communities are suburban and have low overall social vulnerability. However, Hampton and Newport News, also containing military bases, have higher levels in the race and social status and service sector employment factors that subsequently result in higher SoVI values. South of Hampton Roads is Norfolk, Portsmouth, Chesapeake, Suffolk, and Virginia Beach, which surround the large naval bases of Norfolk and Air Station Oceana. Similar to the contrast on the northside of Hampton Roads, Norfolk and Portsmouth's denser cities have higher social vulnerability levels driven by race and social status vulnerability. The adjacent suburb communities of Chesapeake, Suffolk, and Virginia Beach are majority non-Hispanic white and wealthier communities, with lower social vulnerability levels.

Similar contrasts in local geographies of SoVI appear in Petersburg, VA, located outside the main entrance to Fort Lee. Petersburg has the highest SoVI score of all military communities of 7.75, driven by race and social status and service sector employment. Neighboring Prince George County has a SoVI score of -6.33. The range in SoVI values between Prince George County and Petersburg, VA is one of the largest between two neighboring communities in the United States. Therefore, it is a false assumption that military bases reduce social vulnerability in all military communities or do so equally. Communities within the Hampton Roads region and around Petersburg, VA show stark contrasts in their social vulnerability levels, explainable in part by other institutional and economic influences and inequities not captured in SoVI.

The logit model's significant contributing factors of SoVI were also mapped through Anselin Local Moran's I cluster analysis. Increases in the age factor, with variables median age, social security recipients, and age dependency (elderly and young children), were more likely to be associated with non-military communities in the logit model. Age has high clusters in Appalachia, South Florida, Texas, and South Florida (Figure 4.3). 11 out of the 12 (92%) military communities in high age clusters were low outliers, compared to only 44% of non-military communities that were outliers. This adds to the logistic regression finding that age vulnerability is significantly lower in military communities, even when considering location. The one county that was not an outlier in high age clusters was Monroe County, FL, identified earlier as a popular retiree destination. Only one out of the 19 (5%) military communities in low age clusters were high-value outliers, compared to the 36% of non-military communities that were outliers. This further supports the result of military communities having uniquely lower age vulnerability.

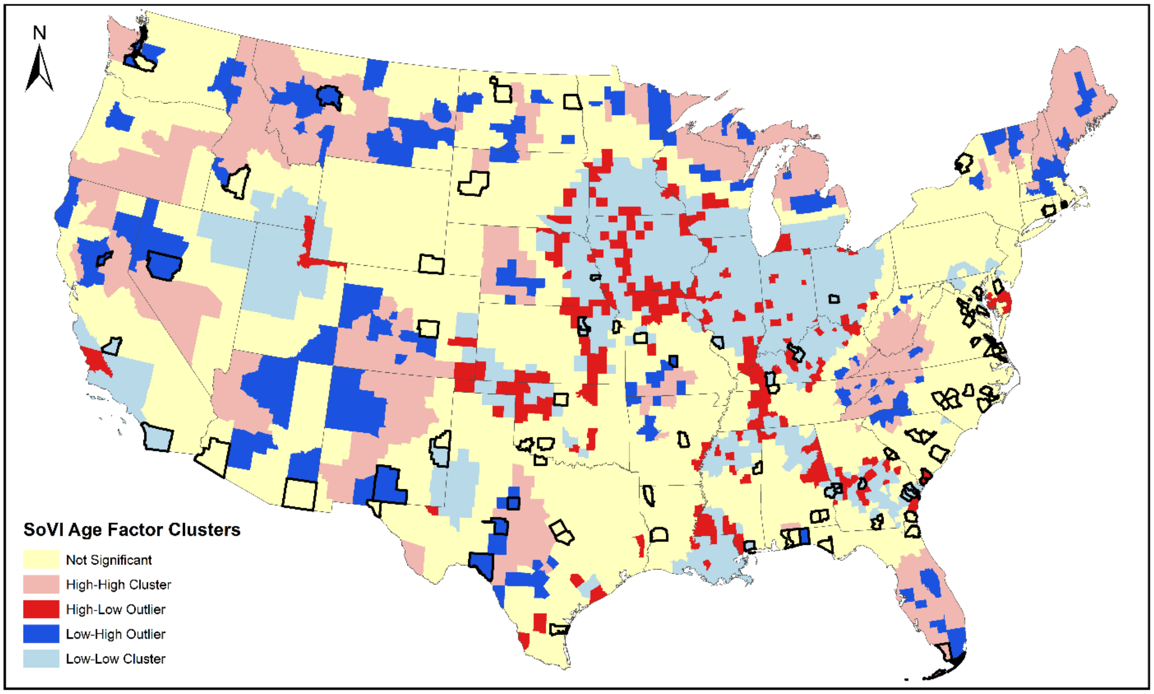

Figure 4.3: Age Factor clusters of social vulnerability (military communities in dark outline).

Service sector employment was another significant factor in the logit model, where higher levels occurred in military communities. High values of service sector employment clustered in the Northeast through the Midwest and the West Coast, while low-value clusters wered found in the Southeast, northern Great Plains, Mountain West (Figure 4.4). In low service sector employment clusters, 35 out of 51 (69%) military communities were high-value outliers compared to only 48% of non-military communities identified as outliers. Conversely, only 10 out of the 38 (26%) military communities in high service sector employment clusters were low-value outliers, compared to 46% of non-military communities that were outliers. The ten low-value outliers in military communities were clustered in the greater D.C. metropolitan area and wealthier suburbs of the Hampton

Roads region, where high-paying wages and more diverse economies exist. The higher percentage of high-value outliers and the smaller percentage of low-value outliers demonstrates that service sector employment is generally higher in military communities, except in the national capital region (NCR), home to the defense industrial complex. The Pentagon, Fort Belvoir, Fort Myer, Marine Corps Base Quantico, and others in the NCR mainly function at the government's strategic level and are staffed by high-ranking officers and senior enlisted non-commissioned officers. Officers have much higher incomes than lower enlisted soldiers, who are more numerous at other military bases outside of the NCR. The high-paying jobs available in the defense industrial complex and demographic makeup of the military communities in the area demonstrated that military communities were not homogeneous and possess different vulnerabilities.

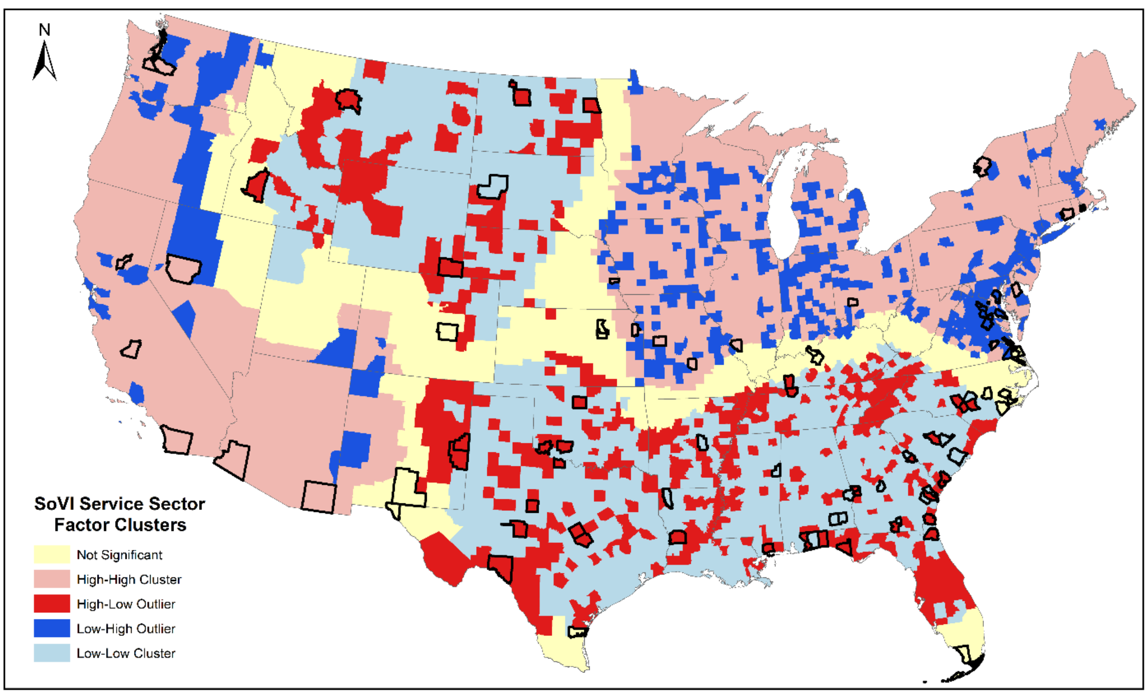

Figure 4.4: Service Sector Factor Clusters (military communities in dark outline).

With variables such as nursing home residents and the number of hospitals per capita, the special needs factor had high-value clusters in the Great Plains stretching down to the Texas Panhandle and West Texas. Clusters of low special needs populations exist in Appalachia, the southwest, and the Pacific Northwest. Only a few outliers were found in military communities as they generally followed the prevailing geographic trend as the communities around them. Few outliers indicate that geographic location may influence the special needs vulnerability more than the military populations and bases themselves. There are also not as many military communities located in the Great Plains, where there are high-value clusters of special needs vulnerability. Other regions have more military communities, such as the South, which have low-value special needs clusters.

The race (African American and social status) factor mostly followed existing geographic clusters as well, with only a few outliers in both high and low-value clusters. As expected, military communities in the South and Mid-Atlantic had higher levels of race and social status vulnerability than military communities in other regions. Low race and social status clusters were found in the Midwest, Great Plains, and Northwest, where there are fewer military communities. There were no military communities identified as outliers in clusters for the wealth factor of social vulnerability, which followed existing geographic patterns. Military communities located in clusters of high wealth, such as in the D.C. metropolitan area, exhibited similar levels of wealth as the neighboring communities in those clusters. There were also fewer and smaller clusters of both high and low wealth throughout the United States.

4.4 DIFFERENCES IN CAPITALS OF BRIC BETWEEN MILITARY AND NON-MILITARY COMMUNITIES

Although no significant differences in community resilience levels between military and non-military communities were identified ($p = .350$), binary logistic regression was conducted to highlight the most influential capitals of resilience in military communities compared to non-military communities. The six capitals of resilience that comprise BRIC are community, social, institutional, infrastructural, economic, and environmental. Again, each capital was standardized by z-scores before the regression analysis. The same random sample of the 212 communities (106 military and 106 non-military) used in the SoVI regression was used in the BRIC regression to remain consistent. As expected, the results of the BRIC logistic regression were not as strong as the SoVI factors but was statistically significant ($\chi^2(5) = 74.2,$ p =.000).

As shown in Table 4.4, three of the six capitals of BRIC significantly contributed to the model. They were community capital, social capital, and environmental capital. Environmental resilience was expected as it includes the variables percent of land in wetlands, average surface perviousness, and food access. Most military communities have large natural areas where the ground is pervious due to undeveloped training areas on military bases, and many are in rural counties. With a one-unit increase in social resilience values, communities were two times more likely to classify as military communities. This could be due to the military service requirement of receiving a high school diploma and benefits such as health insurance coverage, which are some of the social capital variables. A one-unit increase in community capital, which has variables like voting participation and percent of residents born in other states, was 3.76 times more likely to classify a community as non-military. This is likely due to the frequent moves of military members leading to lower levels of place attachment.

Table 4.4. Binary logistic regression results with capitals of BRIC in descending order based on the Wald statistic.

BRIC Capital	***B***	**Wald** χ^2	***p*-value**	**Odds ratio**	**Likely category with one unit increase**
Community	-1.32	37.08	.000	3.76*	Non-military
Social	0.76	10.44	.001	2.13	Military
Environmental	0.36	4.06	.044	1.43	Military
Institutional	0.33	3.09	.079	1.39	Military
Infrastructural	0.29	1.96	.162	1.33	Military
Economic	.015	0.47	.492	1.16	Military

*Inverted odds-ratio

Military communities with high residuals that were incorrectly classified by the model included higher levels of community capital, lower levels of social capital, and more urban communities with lower environmental capital levels. The urban counties of Honolulu, HI and Petersburg, VA, had some of the lowest environmental capital levels in the sample and were incorrectly classified as non-military by the model. Petersburg, VA, Kleberg County, TX, and Cochise County, AZ all had the lowest social capital levels among military communities. In contrast, Sumter County, SC and Hardin County, KY have high levels of social capital. No spatial pattern existed in the residuals, as high and low residuals were in various parts of the country. Looking again at the most military-dominated counties in the U.S., it is clear that lower levels of community capital drive lower overall community resilience in those places (Table 4.5). This finding is similar to those of Cutter and Derakhshan (2020), who identified low community capital as the driver in the least resilient communities in the U.S

Table 4.5. Z-scores of BRIC capitals in the most concentrated military communities.

County	Percent Military Employ.	Social	Econ-omic	Infrast-ructural	Comm-unity	Institut-ional	Enviro-nmental
Chattahoo-chee, GA	52	-0.34	-1.99	0.35	-3.28	-0.52	-0.33
Pulaski, MO	28	0.69	-0.16	-1.42	-1.02	-0.56	-0.28
Onslow, NC	25	0.58	-0.48	-0.03	-0.85	1.19	1.19
Geary, KS	22	1.20	0.54	0.90	-0.03	0.70	-0.16
Christian, KY	14	0.71	-0.28	0.05	-0.14	0.19	-0.48
Vernon Parish, LA	14	0.75	-0.61	-0.86	-0.14	1.73	-0.26
Coryell, TX	14	0.34	-0.66	-0.39	-1.21	-0.15	-0.05
Norfolk, VA	12	-0.05	0.28	1.69	-0.83	0.24	-1.88
Liberty, GA	12	1.00	0.25	-0.58	-0.04	-0.34	1.52
Elmore, ID	12	0.15	0.02	0.03	-1.42	-0.68	-0.29

4.5 SPATIAL ANALYSIS OF COMMUNITY RESILIENCY OF MILITARY COMMUNITIES

Significant clusters of high BRIC scores existed in the upper Great Plains, New England, and southern Louisiana (Figure 4.5). Low BRIC clusters were located throughout the western states, primarily in the southwest and into southern Texas. Smaller clusters of low BRIC existed in pockets of the southeast, including Appalachia and Florida. Only one of seven (14%) military communities located in high BRIC clusters was a low outlier, which was Riley County, Kansas, home to Fort Riley and Kansas State University. Out of the 21 military communities located in low BRIC clusters, 7 were high-value outliers (33%). The outliers were expected, as BRIC values are higher in military communities. The seven outliers of high BRIC values were located in the southeast and central Texas, and no outliers were located in the southwest.

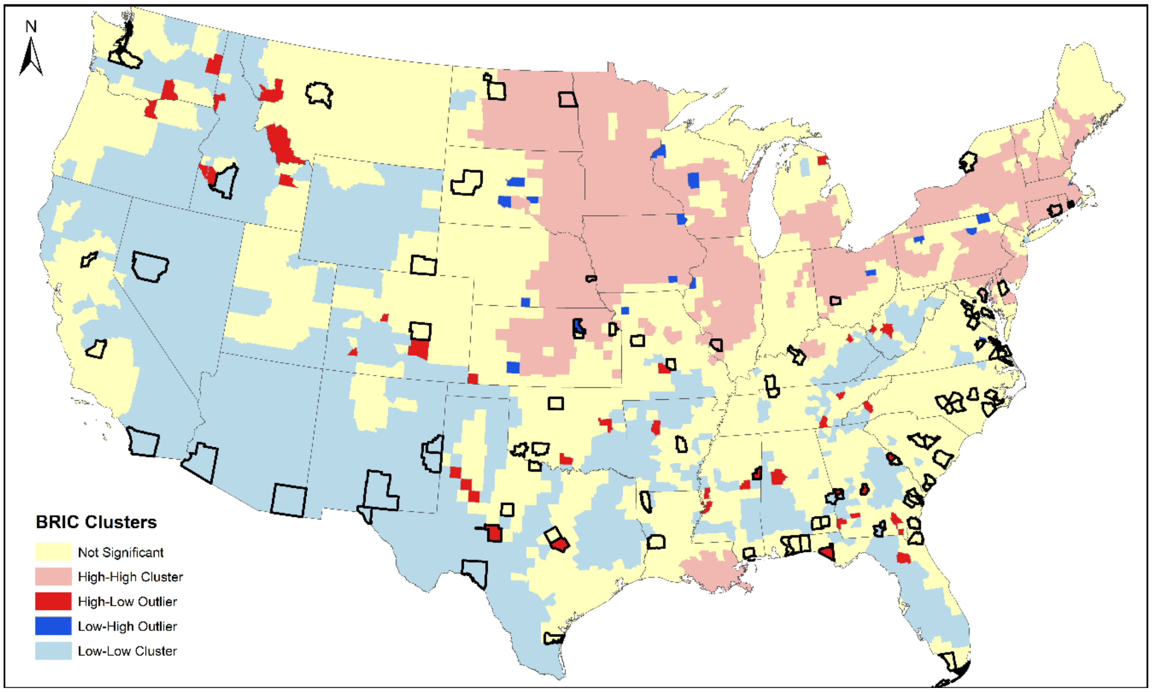

Figure 4.5: Anselin Moran's I output for BRIC clusters (military communities in dark outline).

Community capital was the most influential component of BRIC in the logit model, and higher values were more likely to be associated with non-military communities. Low values of community capital clustered along the West Coast, Southwest, Florida, and others (Figure 4.6). Out of the 33 military communities located in low-value clusters, zero were high-value outliers, while 16% of all non-military communities in low community capital clusters were high-value outliers. This indicated that lower community capital was a trait consistent across military communities. In addition, 8 out of 13 (62%) military communities in high-value clusters were identified as low-value outliers, compared to only 16% of non-military communities. The spatial analysis findings add to the logit model results that identified community capital was uniquely lower in military communities, regardless of prevailing geographic trends.

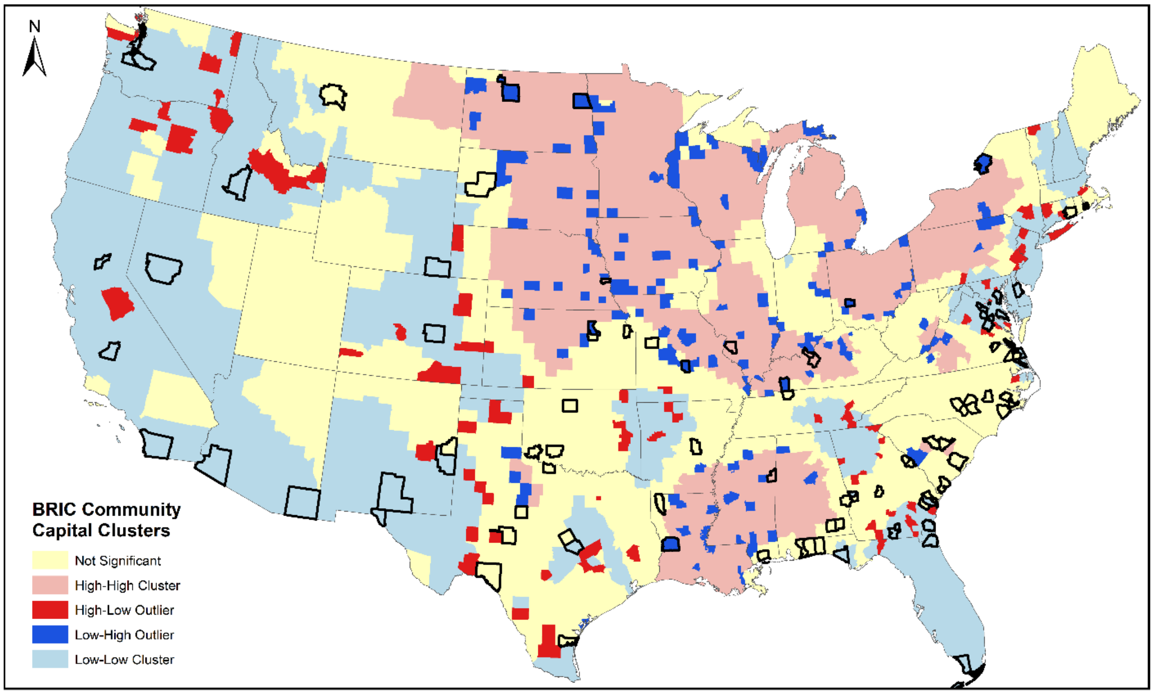

Figure 4.6: Community Capital Clusters (military communities in dark outline).

Social capital, the next most influential variable in the model, had high-value clusters in the Northeast, Midwest, and the Great Salt Lake region (Figure 4.7). Out of the 16 military communities located in clusters of high social capital, zero were low outliers, compared to 5% of non-military communities. Low values of social capital were clustered primarily in the southern U.S., including Florida, south Texas, and the Mississippi River valley. In those areas, 5 out of 13 (38%) military communities were identified as high-value outliers, compared to only 17% of non-military communities. The individual variables in social capital were sociodemographic and economic characteristics such as educational equity, transportation access, food access, and health coverage. Many social capital variables are high in military communities due to enlistment requirements and benefits provided to service members and their families.

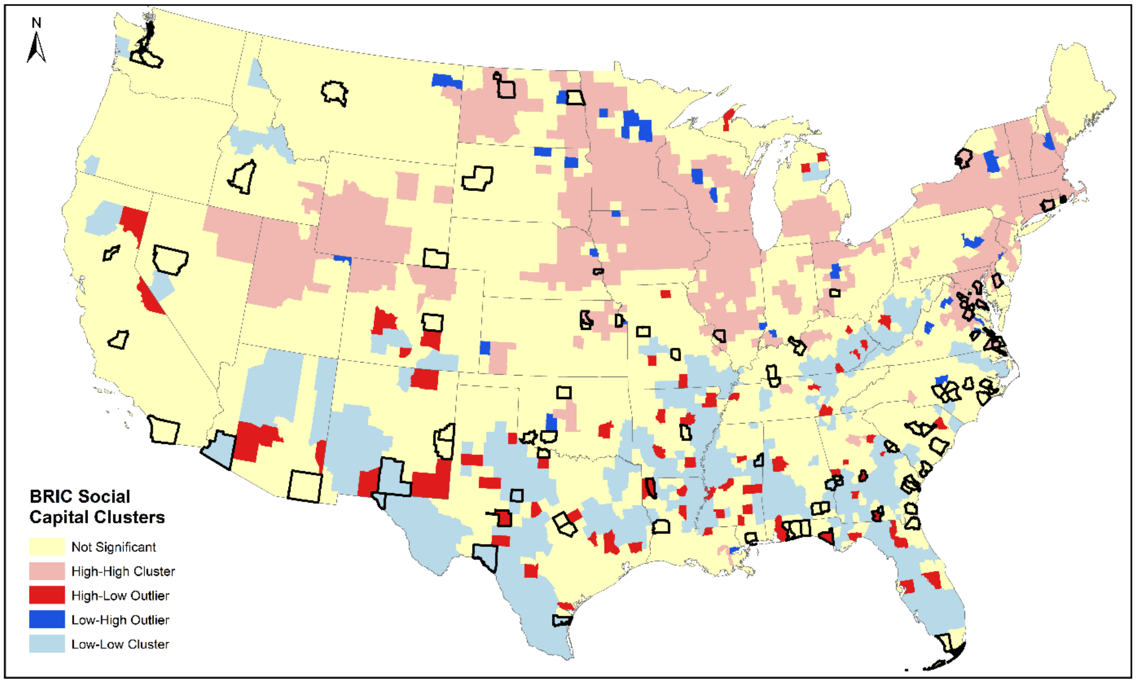

Figure 4.7: Social Capital Clusters (military communities in dark outline).

No significant patterns or outliers emerged from the LISA statistic in environmental capital. Only a few small clusters of high values existed along the coastline (wetlands) and low values in urban areas (perviousness). After conducting the statistical and spatial analysis of the differences between military and non-military communities in resiliency, military communities had uniquely lower levels of community capital than non-military communities, regardless of geographic location. Social capital was higher in military communities but is not as strong as the influence of community capital.

4.6 COMPARING WITHIN MILITARY COMMUNITIES BY MILITARY DEPARTMENT

In addition to identifying differences between military and non-military communities, it is also beneficial to identify differences within military communities, using the service branch represented by the base. This type of analysis helps leaders in the DoD and state and federal governments identify any differences in Army, Air Force, or Navy communities' underlying conditions. Non-parametric tests examined any differences, this time using the Kruskal-Wallis test and multinomial logistic regression. Table 4.6 displays the Kruskal-Wallis test results against the mean ranks of the 93 military communities in the dataset. The 13 Joint communities with multiple types of bases were not included.

Significant differences were found in hazard losses and social vulnerability, while differences in the mean ranks of community resilience were not statistically significant. After conducting multiple comparisons between community types, there were significant differences between Army and Air Force communities in hazard losses. Army communities had lower total losses per capita, while Air Force communities had greater total losses per capita. Interestingly, Navy communities had greater losses per capita on average, but that was due to the outlier of Monroe County, FL ($152,285). Non-parametric statistical tests reduced the impacts of outliers on results, as shown in the mean rank values. When conducting multiple comparisons for social vulnerability, significant differences were found, where Air Force communities had significantly higher SoVI scores than Navy communities.

Table 4.6. Comparing between military community type (Kruskal-Wallis test).

	Military Community Type	N	Mean	Mean Rank	Adjusted *H* Statistic	*p*-value***
Hazard Losses	Army Air Force Navy	34 31 28	$2,950 $8,275 $9,378	40.6* 57.5* 43.2	7.72	.027
SoVI	Army Air Force Navy	34 31 28	-1.13 -0.21 -1.92	45.2 56.6** 38.5**	6.85	.033
BRIC	Army Air Force Navy	34 31 28	2.70 2.76 2.75	40.7 52.7 48.3	3.30	.192

* Differences in the mean ranks of hazard losses between Army and Air Force communities were statistically significant (*p* =.034) ** Differences in mean ranks of SoVI between Air

Force and Navy communities were statistically significant (p =.03) *** Bonferroni correction applied for multiple tests.

4.7 DIFFERENCES IN SOVI FACTORS WITHIN MILITARY COMMUNITIES

Once again, the overall SoVI score was unpacked to identify the factors contributing to the significant differences between communities by type of military base. Multinomial regression was performed using standardized SoVI factors as independent variables and the type of military community (Army, Air Force, and Navy) as dependent variables. Only 84 out of the 106 military communities were included in the model to reconcile differences in the number of Army, Air Force, and Navy communities. The 28 Navy communities were used in the model, along with random samples of 28 Army and 28 Air Force communities. This was done to follow the same binary logit model procedures examining differences between military and non-military communities. The resulting model was statistically significant ($\chi^2(16) = 65.5\,, p = .000$) and correctly identified the different types of military communities 71.4% of the time for Army, 75% for Air Force, and 67.9% for Navy communities.

Wealth (low), race (African American) and social status, and gender were the three factors that significantly contributed to differences in social vulnerability between Navy and Air Force communities (Table 4.7). With a one-unit increase in the wealth (low) factor, communities were 43 times more likely to be classified as Air Force than Navy and 11 times more likely to be classified as Army than Navy communities. As noted earlier in the spatial analysis, military communities generally had similar wealth values as those around them and similar high and low-value clusters (no outliers). Therefore, larger amounts of wealth in Navy communities, or the lack of wealth in Army and Air Force communities, were likely due to Navy communities' geographic location on the coasts.

Only three naval communities had low levels of wealth (Onslow, NC, Yuma, AZ, and Kleberg, TX), and 16 out of the 28 Navy communities had wealth (low) factor scores less than negative 1, indicating high levels of wealth. In contrast, not a single Army and Air Force community had a wealth (low) factor less than negative 1, indicating a lack of wealth comparatively. The existing level of wealth is an essential factor to consider when assessing the communities' ability to prepare and mitigate against adverse disaster outcomes.

Table 4.7: Multinomial logistic regression results with SoVI factors displayed by descending Wald statistic by military community type.

Factor	*B*	Wald χ^2	*p*-value	Odds ratio	Likely category with one unit increase
Significant factors between **Air Force and Navy** (negative denotes AF association)					
Wealth (low)	-3.78	12.9	.000	43.45*	Air Force
Race (African Am. and Social Status)	1.64	5.79	.016	5.12	Navy
Gender (female)	-1.64	4.90	.027	5.13*	Air Force
Significant factors between **Army and Navy** Communities					
Wealth (low)	-2.41	9.14	.002	11.15*	Army
Ethnicity (Hispanic)	.949	.449	.034	2.58	Navy
Significant factors between **Army and Air Force** (negative denotes Army association)					
Race and Social Status	-1.52	8.19	.004	4.57*	Army
Special Needs	2.43	5.24	.022	11.31	Air Force

*Inverted Odds-Ratio

Higher levels of race (African American) and social status were associated more with Army and Navy communities than Air Force communities. A one-unit increase in race and social status vulnerability was about five times less likely to be attributed to Air Force communities. Again, very few outliers existed in the spatial analysis of race and social status, so these differences were most likely due to Army, Air Force, and Navy communities' geographic location. Only about a third of Air Force communities were in the South, compared to two-thirds of all Army communities and three-quarters of all Navy communities. Army and Navy communities were more heavily concentrated in the South, and therefore had higher levels of race and social status vulnerabilities. The special needs factor of social vulnerability was a significant contributor to the model between Army and Air Force communities. With a one-unit increase in the special needs factor, Air Force communities were 11 times more likely to be selected by the model. This was also due to special needs vulnerabilities having high-value clusters in the Great Plains, where more Air Force communities are overall.

4.8 DIFFERENCES IN CAPITALS OF BRIC WITHIN MILITARY COMMUNITIES

The multinomial logit model using the capitals of community resiliency was not significant ($\chi^2(10) = 13.3, p = .208$) and only classified Army communities correctly 54% of the time, Air Force communities 39% of the time, and Navy communities 54%, which was not significantly better than random choice. Community capital was the only significant contributor to the model ($p = .03$). When multiple comparisons were conducted, significant differences were found between Army and Navy communities (B = -.988, Wald χ^2 = 5.65, p = .017). With a one-unit increase in community capital, military communities were 2.7 times more likely to be classified as Army communities than Navy. Navy communities were in the Pacific Northwest, the southwestern U.S., and along the Atlantic Coast, where low community clusters were located. Army communities were located mostly in areas with higher community capital values, such as Kentucky, Alabama, and South Carolina. Only one Navy community had a community capital score greater than the mean, compared to the eight Army communities that met the same criteria.

4.9 HAZARD LOSSES COMBINED WITH SOVI AND BRIC

Comparing SoVI and BRIC scores in communities helped identify communities' underlying conditions but only provided part of the picture. Past economic losses should also be considered when comparing the hazardousness of places. As found earlier, hazard losses are significantly lower in military communities than in others, and Army communities had significantly lower damages than non-military military communities. However, many military communities have experienced significant damages from hazards in the past. Table 4.8 displays the ten military communities with the highest hazard losses per capita from 1960-2018.

Table 4.8. Military communities with the highest hazard losses per capita (1960-2018).

Location	**Major Military Base**	**Crop Losses Per Capita($)**	**Property Losses Per Capita ($)**	**Total Losses Per Capita ($)**
Monroe County, FL	NAS Key West	5,999	146,287	152,285
Grand Forks County, ND	Grand Forks AFB	554	70,938	71,492
Jackson County, OK	Altus AFB	1,113	40,642	41,755
Anchorage, AK	JB Elmendorf-Richardson	1	34,491	34,492
Harrison County, MS	Keesler AFB and NCBC Gulfport	177	34,032	34,209
Santa Rosa County, FL	NAS Whiting Field	326	33,275	33,601
Okaloosa County, FL	Elgin AFB	168	23,330	23,498
Coffee County, AL	Fort Rucker	1,998	13,623	15,621
Escambia County, FL	NAS Pensacola	101	14,350	14,451
Meade County, SD	Ellsworth AFB	560	12,680	13,240

Source: Data compiled by author from SHELDUS

All military communities located along the Gulf of Mexico are within the top ten hazard losses per capita, except for Bay County, FL (top 13). Hurricanes, the most expensive type of hazard in the U.S., have wreaked havoc on military communities in recent years (Gall et al., 2009). Grand Forks County, ND, and Jackson County, OK were two communities that were unexpected to be in the top three due to the relatively little media attention the Midwest receives (Figure 4.8). Grand Forks experienced frequent riverine flooding events along the Red River of the North, while Jackson County, Oklahoma, located along the Red River of the South, experienced severe storms, tornadoes, and periodic flooding. Most of the damages in these communities were due to a singularly large hazard event. In Grand Forks, the 1997 Red River Flood caused over $60,000 in damages per capita while in Jackson County, OK, severe storms and high winds caused over $35,000 in damages per capita in 2008. These single hazard events led to Presidential Disaster Declarations and accounted for over 85% of Jackson and Grand Forks Counties' damages in the 59-year dataset.

Anchorage, Alaska, experienced the deadly 1964 Great Alaskan earthquake, its most damaging event. Anchorage experienced other hazards as well, such as severe winter weather, flooding, and even wildfire. Coffee County, Alabama, located 60 miles from the Gulf, experienced frequent flooding events as well as occasional tornado outbreaks. The 2007 Enterprise, AL tornado was an EF-4 that destroyed the local high school, several hundred homes and businesses, and killed nine people, including the children of soldiers at nearby Fort Rucker (Pitts, 2017). Lastly, Meade County, SD, located on the Black Hills' eastern slope, experienced many hazard types such as flash flooding, wildfires, landslides, severe storms, and winter storms.

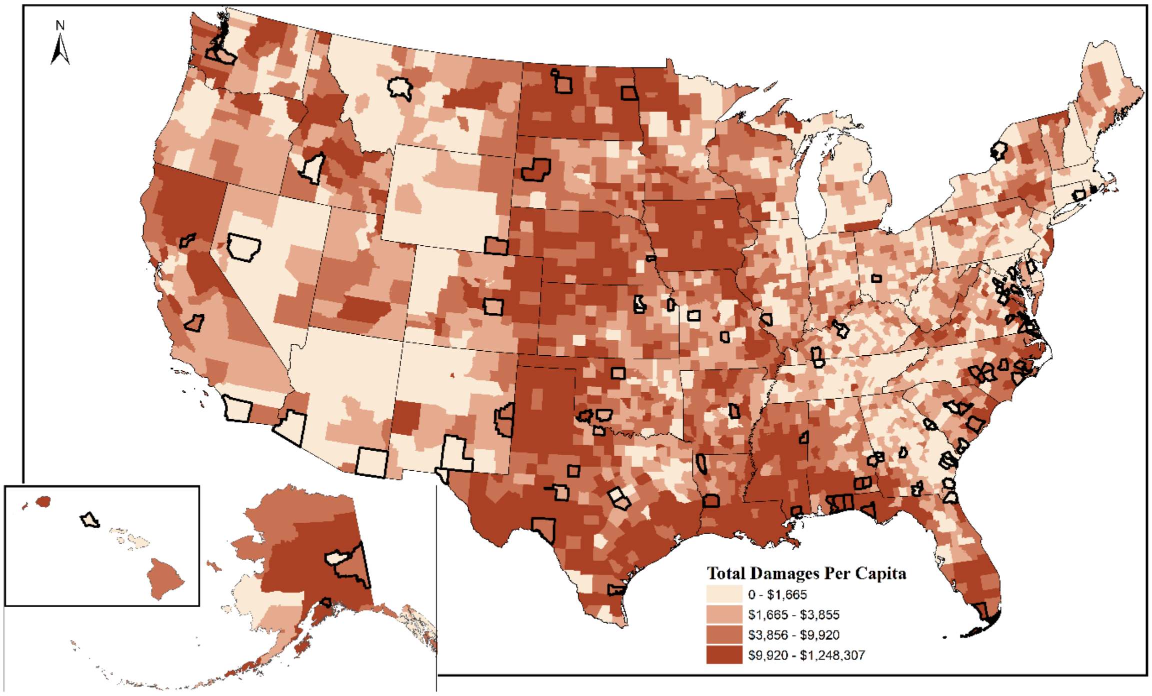

Figure 4.8: Total Losses Per Capita in the United States (1960-2018), military communities in dark outline and hazard losses presented in quartiles.

In addition to a per capita assessment, hazard losses were also adjusted by the size of the county's military population (*total losses per capita* x *number of military members).* Results of this adjustment highlight communities where hazard losses have impacted the most military members. The larger military communities of El Paso County, CO, San Diego County, CA, and Onslow County, NC, replaced smaller military communities of Grand Forks, Jackson, and Coffee Counties in the top ten. The other counties along the Gulf of Mexico and Anchorage, AK, remained. El Paso County, Colorado, with over 30,000 military members, experienced the full spectrum of hazards. Hazard damages in the Colorado Springs area (El Paso County) totaled $3,800 per capita and included losses from flooding, wildfires, winter weather, and severe weather like hail. San Diego County had relatively low damages per capita ($1,473) over the 59-year period, but when multiplied by the 73,000 military members in the county, it demonstrated that the losses have impacted many military families. Compare that to Jackson County, OK, for example, which had only 1,000 military members but a per capita loss of over $40,000. While the losses were greater in Jackson County, fewer military members and families were impacted. San Diego County experienced an increasing amount of hazard losses, however, mostly due to wildfire. Onslow County, NC, is on the east coast and home to Camp Lejeune, a Marine Corps base home to 40,000 service members. Onslow residents experienced frequent flooding events, including large flood losses in 2018 from Hurricane Florence and other hazards like severe weather.

However, hazard losses only show the magnitude of physical damage that a community experienced and does not consider the people who bear the brunt of the losses or how that community recovers. It also skews the results to show counties with singular or a few large-scale hazard events, compared to more frequent but smaller hazard events. While Monroe County, FL experienced the most hazard losses by far, the underlying social vulnerability and resiliency in that county were about average (SoVI = 0.48, BRIC = 2.734) compared to other places. Similarly, El Paso County, CO and San Diego County, CA had lower than average social vulnerability and higher resiliency. Onslow County, NC, on the other hand, had lower social vulnerability but lower resiliency than average, indicating it may not be as resilient as other communities.

When hazard losses were combined with the underlying measures of social vulnerability and community resiliency in a community, the community's hazardousness was assessed. This is not to say that places such as Monroe County, FL are not hazardous or that there are not vulnerable populations within the county; only that when compared at the county level, there are other counties that may face worse consequences if a similar magnitude hazard event were to occur. Table 4.9 displays the five military communities that were above the median level of hazard losses ($3,878), above the median SoVI (.30), and below the median BRIC (2.733). Interestingly, four out of the five are located in the Southwest.

Val Verde County, TX is located along the U.S. and Mexico border and contains Laughlin Air Force Base, a relatively small base used to train future Air Force pilots. As expected, higher social vulnerability in Val Verde was driven by ethnicity (Hispanic) and service sector employment factors. Low community resiliency in Val Verde was driven by lower levels of community and institutional capital. It is a smaller county by population but experienced periodic flooding and severe weather events such as hailstorms that caused significant damages on a per capita basis. When higher levels of social vulnerability and lower levels of resiliency were taken into account, these hazard losses were amplified, and recovery took longer or was uneven within the community. Roosevelt and Curry counties in New Mexico have almost identical drivers of social vulnerability and resilience as Val Verde County, Texas, and experienced similar hazards. These counties border each other and contain Cannon Air Force Base, another smaller-sized base home to an Air Force Special Operations Wing. Kleberg County is another South Texas county and faces similar hazard threats like flooding, but it is located along the Gulf Coast and experiences hurricanes. It has the same drivers of low social vulnerability but also has lower levels of economic resilience.

Table 4.9: Military communities greater or less than median thresholds of SoVI and BRIC respectively, sorted by total hazard losses.

Location	Major Military Base	Hazard Losses Per Capita ($)	Social Vulnerability (SoVI)	Community Resiliency (BRIC)
Roosevelt County, NM	Cannon Air Force Base	7,092	2.7	2.558
Curry County, NM	Cannon Air Force Base	5,728	0.92	2.627
Val Verde County, TX	Laughlin Air Force Base	5,646	5.27	2.553
Kleberg County, TX	Naval Air Station Kingsville	5,452	3.95	2.726
Dale County, AL	Fort Rucker	4,873	0.05	2.695

One of the constants when comparing both Tables 4.8 and 4.9 is the presence of Air Force Bases, Naval Air Stations, and an Army Aviation community (Dale and Coffee County, AL). Airbases, whether Air Force or Navy, appear to be in more hazardous communities overall when accounting for hazard losses, social vulnerability, and resiliency. The Gulf of Mexico and highly rural locations in the West provide the military with large areas over land and sea where aircraft training and missile testing are unfettered. The Gulf locations provide instant access for fighter pilots and warships to conduct training in the Eglin Gulf Test and Training Range, located in the eastern half of the Gulf. This area in the Gulf of Mexico gives the military a vast area to conduct aircraft training and testing, joint exercises, and weapon testing free from the restrictions in place over more populated land areas and more trafficked sea areas (DoD, 2018). However, as mentioned earlier, the coastal airbases along the Gulf are primarily located directly on the water and shoreline, making them extremely vulnerable to storm surge, wind damage, and flooding from hurricanes (Figure 4.9). NAS Kingsville, Keesler AFB, NAS Pensacola, Eglin AFB, Tyndall AFB, NAS Key West, and even more inland locations such as Fort Polk, Louisiana, and Fort Rucker, Alabama, have experienced significant damages from hurricanes in the past.

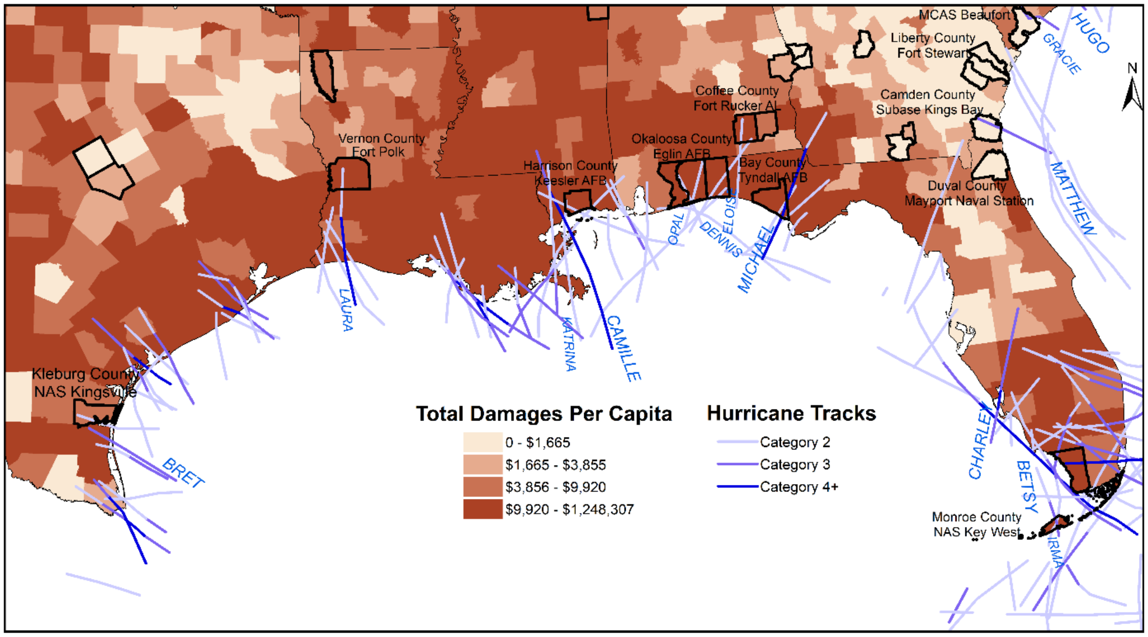

Figure 4.9: Hurricanes and Military Communities along the Gulf of Mexico. Labeled tracks are select hurricanes that have significantly impacted military communities and hazard losses are from all hazards, data from NOAA's IBTrACS database (Knapp et al., 2018).

Flooding due to extreme precipitation and continued human development, as well as the frequency of major hurricanes, are likely to continue and increase in the future (Wuebbles et al., 2014). Communities with a severe risk to hazards like hurricanes are ideal targets for military and local community partnerships to decrease overall disaster risk. Public-private partnerships (PPPs) effectively reduce the costs of projects designed to increase local communities' resilience to hazards (Twigg, 2015). The essential ties between military bases and local communities can be strengthened by using PPPs to decrease their vulnerability and increase their resilience to hazards.

4.10 SUMMARY OF RESULTS

The combination of both statistical and spatial analysis resulted in a variety of significant findings in the hazardousness of military communities in the United States.

First, significant differences were found between military and non-military communities in hazard losses and social vulnerability. The differences in hazard losses were primarily explained by military communities' geographic location, whereas many factors, including location, influenced social vulnerability in military communities. The factor of social vulnerability found to be the most influential in explaining these differences was age, where military communities have lower age vulnerability and were low spatial outliers in high age clusters. The service sector employment factor in SoVI was also an influential variable in the regression model where communities with higher service sector vulnerability were more likely classified as military. This was also moderately consistent across geographies, except in the national capital region.

Second, there were significant differences in social vulnerability between the type of military community. Communities with Air Force bases had significantly higher SoVI scores overall, especially when compared to Navy communities. The wealth (low) factor drove these differences in SoVI, where Navy communities had significantly higher wealth than Army and Air Force communities, thus reducing their relative levels of social vulnerability. Race (African American and social status) was also a significant contributing factor. Air Force communities had a significantly lower race (African American) and social status vulnerability than Navy and Army communities. This was also a function of location. Fewer Air Force communities are located in the South, with its historical background of higher levels of African Americans and lower-income populations.

Third, there was no significant difference between military and non-military communities and between types of military communities in community resilience. However, community capital was lower in military communities overall, with increasing community capital levels more likely to represent non-military communities. In military-dominated counties, community capital was the lowest capital of resilience in those places. The differences in community capital were mostly consistent regardless of geographic location, with just over half of military communities in high-value clusters identified as low-value outliers. Within military communities, Navy communities had significantly lower levels of community capital than Army communities. However, this was reflective of geographic location. Army communities are mostly in high community capital clusters (Southeast), and Navy communities are located along the coast where there are lower community capital levels.

Lastly, military communities along the Gulf of Mexico and select military communities in Alaska and the Dakotas have experienced the most hazard losses per capita. When hazard losses, social vulnerability, and resilience levels were analyzed together, aviation hubs in South Texas, New Mexico, and Dale County, AL were most at risk for adverse disaster outcomes. This was driven by the combination of high Hispanic ethnicity, high service sector employment, and low levels of community capital. In general, military communities along the Gulf of Mexico were most at risk to hazards and will likely continue to be in the future.

CHAPTER 5

DISCUSSION AND CONCLUSION

Previous studies related to hazards and militaries identified the military's role in emergency management. A smaller amount of literature identified how military bases assist local communities in disaster response and initial recovery. The primary goal of this research was to understand how military bases influence the underlying conditions of disaster risk in their communities and the drivers producing that risk. Doing so was a crucial first step in understanding military communities' overall hazardousness and identifying communities that may require greater assistance in reducing risk in their communities. Counties were identified as military communities, and then a variety of statistical and spatial tests and analyses were conducted, including logistic regression and Anselin Local Moran's I.

Results were robust in that military communities have lower social vulnerability than other communities driven by their lower age vulnerability. The primary factors increasing the social vulnerability of military communities were service sector employment and race (African American and social status). Higher levels of service sector vulnerability were in military-dominated communities, and Air Force communities had the highest overall social vulnerability levels out of all defense service branches. In community resiliency, community capital is the primary driver of lower resilience within military communities, although military communities had higher resiliency levels than non-military communities. This finding bridged knowledge from hazards researchers that identified community capital as necessary for resilient communities with those of psychologists, who studied the connections between military families and the local community as key to building resilience at the individual level.

These findings are helpful on several levels. At a basic level, it shows that military communities are unique places and that military bases and their influence should not be overlooked or ignored when conducting hazard research or in practice. It also identified the factors contributing to military communities' lower social vulnerability and greater resiliency to hazards. This can help county, state, federal emergency managers, NGOs, and the Department of Defense allocate funding, prioritize mitigation and resilience projects, and determine what types of outreach and educational programs should be conducted to maximize benefits. At a more profound level, it signifies that there are inequities in the levels of social vulnerability and resilience within military communities that extend beyond differences in geographic location, such as the differences between neighboring places around Petersburg and the Hampton Roads region of Virginia.

There are several limitations and shortcomings from this research. The local impacts and differences in military communities were not observed or were muted at the county level, except in smaller county geographies and independent cities like Petersburg, VA. A finer scale of analysis would have improved the results and findings in places like Beaufort County, SC, due to the large retirement population on Hilton Head Island. Beaufort County includes Hilton Head and Port Royal Island, the latter home to two military bases and a younger population, with very different vulnerabilities than the island of Hilton Head. Also, hazard losses were biased towards more extensive, more extreme events like hurricanes. The impacts from less costly and more frequent events were subdued. Frequent events may not cause extensive direct economic damages but cause indirect damages connected to school and road closures in communities, for example.

Another limitation of the research is that the regression models did not directly address spatial autocorrelation. As mentioned previously, this omission is partly addressed by using Anselin Local Moran's I to identify spatial outliers, which is useful when spatial autocorrelation is present in the data (Anselin, 1995). Lastly, the data did not account for the future impacts of anthropogenic climate change and its association with climate-sensitive hazards. This may have underestimated some coastal locations' hazardousness, such as the Hampton Roads, which are under severe threat from sea-level rise, and even underestimated the hazardousness of more continental locations, which are at risk to drought in a warming climate.

Many other aspects regarding the vulnerability and resilience in military communities were not captured in this research. Military bases create other political, institutional, and environmental vulnerabilities in communities. Although not the focus of this research, they are briefly described below:

•The potential of future base realignment and closure commissions (BRAC) or troop and mission reductions on military bases is a constant threat. Communities spend money to 'BRAC proof' their communities (Sorenson, 2018). Hazards also influence BRAC decisions (Dixon, 1994).

•Pollution from toxic chemicals, waste, and pollutants on military bases impact local communities (Davis et al., 2007). The impacts of pollution have also been evidenced at former military sites (Kopack, 2019).

•Civilians cannot receive compensation from federal entities under the discretionary exclusion of the Federal Tort Claim Act. A dam failure was partially attributed to the base commander's actions at Fort Jackson in 2015, flooded downstream off-base homes, and the homeowners could not be compensated for those damages (US Court of Appeals, 2020; Hamilton, 2016).

•Department of Defense installations do not pay property taxes on their land or provide any payment in lieu of taxes (PILT) to local communities (H.R.4710). Non-resident military members are also exempt from state income taxes. The impact of these foregone payments on communities to their underlying vulnerability and resiliency is unknown.

There are also other positive influences on resiliency and vulnerability in military communities not captured in this research. These include:

•The newly established military infrastructure resilience (MIR) and defense community infrastructure pilot program (DCIP) provides additional funding sources in military communities to increase infrastructure resilience (Congressional Research Service, 2020).

•Mutual aid agreements can help speed up the initial recovery in local communities and disaster response (Trivedi, 2020).

•Additional funding and support for local school districts are available for military communities (Buddin, 2001).

This research was premised on the belief that the Department of Defense and local communities have a shared responsibility to reduce disaster risk in their communities and identified the factors in which local communities and military bases can reduce that risk

(NRC, 2012). To meet the challenges in a future climate and to create resilient military communities, partnerships need to go beyond emergency response and initial recovery. Doing so will not only increase the resilience in the community, but also the resilience of the nation's military.

The top-down approach used in this research was necessary to understand and compare military communities' current hazardousness across the U.S. However, it should not be used as a replacement for local hazard assessments and mitigation plans. As local communities and military bases continue to work together to increase resilience in their communities, more guidance, direction, and funding are required at the federal level to set goals, standards, and equitable policies for all military communities, especially in the face of global climate change. Future directions of research in hazards and military communities include assessing vulnerability and resilience over time, especially before and after base closures or severe hazard events; conducting localized case studies that identify how military bases influence all phases of the disaster cycle; the effectiveness of PPP's to reduce disaster risk reduction, such as those approved by the MIR and DCIP programs; and on other political and institutional influences on vulnerability and resilience in military communities that create or reduce disaster risk. Hazards research in communities that ignore a military base's presence are likely to miss critical factors influencing their vulnerability and resiliency, as they were shown to be unique places in the landscape.

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APPENDIX A

VARIABLES AND FACTORS IN SOVI

This appendix identifies the dominant variables used as indicators in SoVI and the resulting component the variables loaded on after principal component analysis. More information can be found at the Hazards and Vulnerability Research Institute website at https://artsandsciences.sc.edu/geog /hvri.

Table A.1: Variables and Factors in SoVI

Component	Variables
Race (African American and Social Status)	Percent Black Percent female headed households Percent poverty Percent civilian unemployment Percent with less than 12th grade education Percent of housing units with no car Percent renters Percent mobile homes Percent children living in 2-parent families (-)
Wealth (-)	Median house value Percent households earning over $200k annually Median gross rent Per capita income Percent Asian
Dependence and Age (Elderly)	Median age Percent population under 5 years or 65 and over Percent households receiving social security benefits Percent unoccupied housing units People per unit (-)
Ethnicity (Hispanic and Education)	Percent Hispanic % speaking English as 2nd language w/ limit. proficiency Percent with less than 12th grade education

Ethnicity Cont.	Percent of pop. without health insurance (county level)
Special Needs Populations	Hospitals per capita (county level only) Nursing home residents per capita Percent employment in extractive industry
Race (Native American)	Percent Native American
Service Sector Employment	Percent employment in service industry Percent female participation in labor force
Female	Percent female

APPENDIX B

VARIABLES AND CAPITALS IN BRIC

This appendix shows indicators of community resilience and the corresponding capital that were used in BRIC. More information can be found at the Hazards and Vulnerability Research Institute website at https://artsandsciences.sc.edu/geog /hvri.

Table B.1: Variables and Capitals in BRIC

Capital	Indicator	
Social	Educational Equity Age Transportation Access Communication Capacity Language Competency	Health Coverage Mental Health Food Access Health Access Special Needs
Economic	Housing Capital Employment Income and equality (race/ethnicity) Primary and Tourism Employment dependence Federal Employment	Business Size Multi-purpose retail
Institutional	Mitigation Spending Flood Insurance Coverage Jurisdictional Uniformity Disaster Aid Experience Public Disaster Training	Distance from state capital Intercounty partnerships Population stability Nuclear accident planning Crop Insurance
Infrastructural	Housing type Temporary housing availability Medical capacity Access/Evacuation Potential Internet Access	Housing age Sheltering needs Recovery Industrial Re-supply
Community	Place attachment (immigrants) Place attachment (tenure) Political engagement Citizen disaster preparedness and response skills	Religious involvement Civic involvement Disaster volunteerism

Environmental	Food Access/Self Sufficiency Natural buffers Energy use	Pervious surfaces Water stress

APPENDIX C

DATA FOR MILITARY COMMUNITIES

This appendix shows the values for hazard losses per capita, SoVI, and BRIC for each of the 106 counties that were classified as military counties. This is included so that readers can explore and understand the hazardousness of other places not mentioned or referenced in the analysis. Communities are displayed in ascending order by FIPS code (not shown)

Table C.1: Hazard Losses, SoVI, and BRIC in military communities

County, State	Major Military Base	Hazard Losses Per Capita ($)	SoVI	BRIC
Coffee County, AL	Fort Rucker	15,621	-0.5	2.743
Dale County, AL	Fort Rucker	4,874	0.05	2.695
Russell County, AL	Fort Benning	2,463	1.08	2.665
Anchorage Municipality, AK	JBER	34,492	-3.69	2.607
Fairbanks North Star, AK	Fort Wainwright	462	-5.09	2.422
Southeast Fairbanks, AK	Fort Greely	5,330	-1.87	2.253
Cochise County, AZ	Fort Huachuca	1,173	1.94	2.474
Yuma County, AZ	MCAS Yuma	914	3.34	2.394
Lonoke County, AZ	Little Rock AFB	3,913	-2.71	2.762
Kings County, CA	NAS Lemoore	6,150	-0.24	2.572
San Diego County, CA	Camp Pendleton	1,474	-2.72	2.580
Yuba County, CA	Beale AFB	7,027	-0.81	2.717
El Paso County, CO	Fort Carson and Peterson AFB	3,800	-3.41	2.697
New London County, CT	Sub-Base New London	494	-1.34	2.904
Kent County, DE	Dover AFB	1,332	-0.66	2.863

Bay County, FL	Tyndall AFB	10,322	0.85	2.813
Duval County, FL	Mayport Naval Station	226	0.23	2.790
Escambia County, FL	NAS Pensacola	14,451	-0.3	2.778
Monroe County, FL	NAS Key West	152,285	0.48	2.735
Okaloosa County, FL	Elgin AFB	23,498	-1.05	2.718
Santa Rosa County, FL	NAS Whiting Field	33,601	-3.97	2.742
Bryan County, GA	Fort Stewart	1,081	-3.95	2.885
Camden County, GA	Sub-Base Kings Bay	1,315	-2.49	2.734
Chattahoochee County, GA	Fort Benning	931	-8.07	2.467
Columbia County, GA	Fort Gordon	589	-4.82	2.736
Houston County, GA	Robins AFB	496	-1.5	2.798
Lanier County, GA	Moody AFB	3,760	0.55	2.682
Liberty County, GA	Fort Stewart	1,649	0.34	2.789
Long County, GA	Fort Stewart	1,421	-3.24	2.597
Lowndes County, GA	Moody AFB	899	0.27	2.730
Muscogee County, GA	Fort Benning	359	1.8	2.748
Richmond County, GA	Fort Gordon	505	2.8	2.766
Honolulu County, HA	Pacific Command	587	-4.27	2.570
Elmore County, ID	Mountain Home AFB	1,588	-1.31	2.625
St. Clair County, IL	Scott AFB	1,959	0.26	2.850
Geary County, KS	Fort Riley	949	-0.51	2.847
Leavenworth County, KS	Fort Leavenworth	1,749	-4.44	2.804
Riley County, KS	Fort Riley	1,034	-2.43	2.713
Christian County, KY	Fort Campbell	2,484	-0.12	2.723
Hardin County, KY	Fort Knox	1,007	-1.63	2.885
Meade County, KY	Fort Knox	1,652	-4.75	2.749
Bossier Parish, LA	Barksdale AFB	5,036	-1.4	2.818
Vernon Parish, LA	Fort Polk	10,498	-2.38	2.722
Anne Arundel County, MD	Fort Meade/USNA	441	-6.18	2.841
St. Mary's County, MD	NAS Patuxent River	2,528	-5.5	2.831
Harrison County, MS	Keesler AFB	34,209	1.85	2.783
Lowndes County, MS	Columbus AFB	8,526	0.8	2.749
Johnson County, MO	Whiteman AFB	1,617	-1.59	2.719
Pulaski County, MO	Fort Leonard Wood	3,418	-4.09	2.588
Cascade County, MT	Malmstrom AFB	275	-0.16	2.886

Sarpy County, NE	Offutt AFB	2,400	-4.58	2.965
Churchill County, NV	NAS Fallon	215	-0.17	2.626
Curry County, NM	Cannon AFB	5,728	0.92	2.627
Otero County, NM	Holloman AFB	357	2.4	2.530
Roosevelt County, NM	Cannon AFB	7,092	2.7	2.558
Jefferson County, NY	Fort Drum	1,234	-0.73	2.775
Camden County, NC	NSA Hampton Roads	7,724	-3.28	2.858
Craven County, NC	MCAS Cherry Point	4,062	-0.22	2.794
Cumberland County, NC	Fort Bragg	2,075	0.19	2.783
Harnett County, NC	Fort Bragg	4,656	-1.44	2.707
Hoke County, NC	Fort Bragg	11,742	-0.78	2.704
Moore County, NC	Fort Bragg	4,915	0	2.674
Onslow County, NC	MCB Camp Lejeune	2,706	-3.18	2.771
Wayne County, NC	Seymour Johnson AFB	5,064	1.48	2.805
Grand Forks County, ND	Grand Forks AFB	71,492	-1.36	2.927
Ward County, ND	Minot AFB	5,999	-3.2	2.899
Greene County, OH	Wright-Patterson AFB	1,665	-2.56	2.845
Comanche County, OK	Fort Sill	1,687	0.08	2.697
Garfield County, OK	Vance AFB	1,767	1.05	2.816
Jackson County, OK	Altus AFB	41,755	2.77	2.746
Newport County, RI	Naval Station Newport	1,833	-1.58	2.815
Beaufort County, SC	MCAS Beaufort	1,244	0.59	2.670
Berkeley County, SC	Joint Base Charleston	9,597	-3.32	2.783
Richland County, SC	Fort Jackson	775	-0.62	2.853
Sumter County, SC	Shaw AFB	8,596	0.63	2.819
Meade County, SD	Ellsworth AFB	13,240	-4.34	2.777
Montgomery County, TN	Fort Campbell	1,175	-2.44	2.725
Bell County, TX	Fort Hood	2,671	-0.12	2.742
Coryell County, TX	Fort Hood	1,354	-1.46	2.625
El Paso County, TX	Fort Bliss	1,125	5.39	2.592
Kleberg County, TX	NAS Kingsville	5,452	3.95	2.726
Taylor County, TX	Dyess AFB	5,875	1.71	2.778
Tom Green County, TX	Goodfellow AFB	3,645	0.68	2.764
Val Verde County, TX	Laughlin AFB	5,646	5.27	2.553
Wichita County, TX	Sheppard AFB	1,855	0.89	2.776

Caroline County, VA	Fort A P Hill	884	-3.02	2.765
King George County, VA	NSF Dahlgren	3,767	-6.16	2.844
Prince George County, VA	Fort Lee	4,176	-6.33	2.834
Prince William County, VA	MCB Quantico	546	-6.23	2.720
Stafford County, VA	MCB Quantico	1,460	-8.07	2.743
York County, VA	JBLE	3,178	-5.24	2.798
Alexandria city, VA	Pentagon	353	-2.67	2.655
Chesapeake city, VA	Norfolk Naval Station	512	-4.02	2.883
Hampton city, VA	JBLE	1,307	0.55	2.809
Newport News city, VA	JBLE	1,119	1.07	2.768
Norfolk city, VA	Norfolk Naval Station	803	0.12	2.706
Petersburg city, VA	Fort Lee	3,053	7.75	2.873
Poquoson city, VA	JBLE	6,213	-5.86	3.012
Portsmouth city, VA	Norfolk Naval Station	1,595	1.82	2.870
Suffolk city, VA	Norfolk Naval Station	3,608	-2.44	2.900
Virginia Beach city, VA	NAS Oceana	947	-3.24	2.757
Island County, WA	NAS Whidbey Island	939	-2	2.652
Kitsap County, WA	Shipyard Puget Sound	2,131	-3.76	2.697
Pierce County, WA	JBLM	1,682	-2.91	2.743
Thurston County, WA	JBLM	7,196	-2.75	2.728
Laramie County, WY	F E Warren AFB	4,104	-2.63	2.766